

1 Investigating the genetic control of plant 2 development under speed breeding conditions

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15 **Abstract**

16 Speed breeding is a powerful tool to accelerate breeding and research
17 programmes by shortening generation time and has been widely
18 adopted for a range of crop species. Despite its success and growing
19 popularity with breeders the genetic basis of plant development
20 under speed breeding remains unknown. In this study, we explored
21 how genotypes respond in terms of developmental advancement
22 under different photoperiod regimes in the context of speed breeding.
23 A subset of the barley HEB-25 Nested Association Mapping population
24 was evaluated for days to heading and maturity under two contrasting

25 photoperiod conditions: 1) Speed Breeding (SB) consisting of 22 hours
26 of light and 2 hours of darkness), and 2) Normal Breeding (NB)
27 consisting of 16 hours of light and 8 hours of darkness. GWAS revealed
28 that developmental responses under both conditions were largely
29 controlled by two loci: *PPDH-1* and *ELF3*. Allelic variants at these genes
30 determine whether plants display early flowering and maturity under
31 both NB and SB. At key QTL regions, domesticated alleles were
32 associated with late flowering and maturity in NB and early flowering
33 and maturity in SB, whereas wild alleles were associated with early
34 flowering under both conditions. We hypothesise that this may be
35 related to the dark dependent repression of *PPD-H1* by *ELF3* which
36 might be more prominent in NB conditions. Furthermore, by
37 comparing development under two contrasting photoperiod regimes,
38 we were able to derive an estimate of plasticity for the two traits.
39 Interestingly, plasticity in development was largely attributed to allelic
40 variation at *ELF3*. Our results have important implications for our
41 understanding and optimisation of speed breeding protocols
42 particularly when incorporating genetics from wild relatives into
43 breeding programmes and the design of breeding programmes to
44 support the delivery of climate resilient crops.

45 Introduction

46 The world's food demand is expected to rise significantly by 2050, by
47 as much as 56% (van Dijk et al., 2021). This increase is primarily due to
48 the combined effects of climate change, population growth, and
49 global food supply disruptions. To meet this demand, it is essential to
50 increase crop yields sustainably (Smith, 2013). This has been achieved
51 in the past through a combination of improved management practices
52 and the generation of superior germplasm (Cooper et al., 2020;
53 Fradgley et al., 2023). However, recent advances in high-throughput
54 genotyping and phenotyping technologies have opened up new
55 opportunities to accelerate the rate of genetic gain in crops (Li et al.,
56 2018). By reducing crop generation time and using marker-assisted
57 selection and genomic prediction, breeders can now significantly
58 increase the yield potential of crops (Gosal et al., 2020). This has
59 prompted breeders to accelerate the seed to seed time of crops
60 through the deployment of technologies to support rapid generation
61 cycling, such as shuttle breeding, single seed descent, double haploid
62 and, more recently, speed breeding (Watson et al., 2018).

63 Prior to speed breeding, the main technology for faster breeding
64 cycles was the use of double haploid technology (DH), which quickly
65 generated homozygous lines after F1 or F2 generations. However, DH
66 has two main drawbacks: firstly it requires expensive tissue culture
67 labs, secondly DH populations derive from low recombination events

68 and cross-over rates, which increases the population size needed
69 (Inagaki et al., 1998). Moreover, its effectiveness varies among
70 genotypes as often many genotypes are non-responsive to tissue
71 culture (Hooghvorst et al., 2021). Alternatively, single seed descent
72 (SSD) method was adopted in many crops. Traditionally, the SSD
73 approach involves advancing each F2 individual through selfing in a
74 controlled environment with a 16-hour photoperiod for long day
75 plants, achieving up to three generations per year. This method comes
76 with reduced costs and higher genetic variability compared to DH
77 breeding. The increased genetic diversity that results from SSD
78 contributes to improved selection efficiency and serves as a protective
79 measure against genetic drift. As a result, SSD is a powerful tool for
80 enhancing the overall efficacy and success of crop improvement
81 programs. However, SSD is not always a superior alternative to DH as
82 it leads to slower development of recombinant inbred lines (Caligari
83 et al., 1987; Powell et al., 1986).

84 Although research on the effects of extended photoperiod on plant
85 growth and development began almost a century ago (Arthur et al.,
86 1930; Garner and Allard 1927), it was not until recently that
87 researchers began to investigate the most efficient combination of
88 environmental factors for reducing the breeding cycle. Watson et al.,
89 (2018) demonstrated that speed breeding methods could be adapted
90 to reduce generation time for a broad range of crop species.

91 Developing an efficient speed breeding protocol involves optimising
92 several environmental factors, with a key one being the exposure to
93 prolonged photoperiods for long-day species. Speed breeding can be
94 integrated with other technologies to achieve different breeding
95 objectives such marker assisted selection (MAS) for simple traits as
96 genomic selection (GS) for complex traits (L. T. Hickey et al., 2017,
97 2019; Pandey et al., 2022). A body of research has advanced speed
98 breeding protocols aiming to reduce the breeding cycle in long- and
99 short-day plants using controlled environments (Cazzola et al., 2020;
100 Chiurugwi et al., 2019; Fang et al., 2021; Watson et al., 2018; J. M.
101 Hickey et al., 2017; Mobini et al., 2020; Samineni et al., 2020; Schilling
102 et al., 2023). Depending on the species, an optimized protocol can
103 reduce the time from crossing to testing to 18 months or two years,
104 much shorter than SSD or shuttle breeding. Furthermore, speed
105 breeding offers significant advantages over DH technology as it
106 maintains higher recombination and cross-over events while still
107 achieving a similar reduction in generation time at a reduced cost. As
108 a result, rapid cycling protocols have become popular in plant
109 breeding programs around the world.

110 Despite the recent success of speed breeding, there are still
111 opportunities for refinement by optimizing energy and management
112 costs, as the tool is still in its infancy. This is intertwined to the limited
113 understanding underlying the genetics of plant development under

114 such conditions. Specifically, we do not know whether flowering and
115 maturity under very long days (e.g., 22 hours light in speed breeding
116 conditions) is genotype-dependent and under different genetic
117 controls compared to standard long days (e.g., 16 hour days).
118 Understanding this could help breeders and researchers to develop
119 more effective speed breeding protocols. Enhancing our knowledge
120 on this matter can significantly influence the decision-making process
121 for breeders and researchers when considering the adoption of this
122 technology, leading to more effective and targeted crop improvement
123 and research strategies. While studies on speed breeding in cereals
124 have shown that plant development can be accelerated under these
125 conditions (Cha et al., 2022; Watson et al., 2018), experiments have
126 mainly focussed on modern or elite germplasm. As introgression
127 breeding is becoming a valuable tool for gaining access to wild genetic
128 diversity that can help crops adapt to climate change (Gramazio et al.,
129 2021; Hao et al., 2020; Hernandez et al., 2020; Khan et al., 2023; Zhang
130 et al., 2023). Therefore, a better understanding of the genetics of
131 speed breeding would help pre-breeders develop protocols that are
132 effective in these programs.

133 To shed light on the genetic basis of speed breeding, the present study
134 examined the ‘Halle Wild Barley’ (HEB-25) nested associated mapping
135 (NAM) population, which segregates for both wild and domestic
136 alleles (Maurer et al., 2015). The lines were phenotyped for key

137 developmental traits under both **speed breeding** (22 hours of light
138 and 2 hours of darkness) and **normal breeding** (16 hours of light and
139 8 hours of darkness). Data from these experiments and whole-
140 genome marker data using the Infinium iSelect 50k SNP chip (Maurer
141 and Pillen 2019) was used in Genome Wide Association (GWAS) to
142 identify genetic loci associated with the differential responses of
143 spring barley lines grown under the two different artificial growth
144 conditions. To our knowledge, this is the first study to identify the
145 genetic basis of plant development under speed breeding, providing
146 insight into the mechanisms controlling the plant's development-
147 related traits under long and very long days. The results of this study
148 have important implications for the deployment of speed breeding to
149 accelerate the utilisation of genetic diversity, particularly wild
150 relatives, to support the development of future crops.

151 **Material and methods**

152 **Plant material**

153 The present study uses the multiparent nested associated mapping
154 (NAM) population 'Halle Wild Barley' (HEB-25), developed by Maurer
155 et al., (2015). This population was generated using 25 wild barley
156 parents (24 *Horderum vulgare* ssp. *spontaneum*, Hsp and 1 *Hourdeum*
157 *vulgare* ssp. *agriocrithon*) crossed with spring barley cultivar Barke (*H.*
158 *vulgare* ssp. *vulgare*, Hv). The resulting generation was backcrossed
159 with the female parent Barke, following three generations of selfing

160 through single seed descent (BC_1S_3). Thereupon, the deriving lines
161 were propagated through the 6th generation of selfing ($BC_1S_{3:6}$).
162 Further details on the population development is provided in Maurer
163 et al., (2015). This multiparent NAM population has become a crucial
164 genetic resource for investigating various essential traits in barley,
165 including stress tolerance and yield (Büttner et al., 2020; Mehnaz et
166 al., 2021; Saade et al., 2016; Sharma et al., 2018; Wiegmann et al.,
167 2019). In our study, we aimed to efficiently evaluate the HEB-25 to
168 study the genetics of speed breeding. However, screening the entire
169 population in a glasshouse posed practical limitations. To overcome
170 this issue, we implemented a random sampling approach to select a
171 subset of 190 genotypes from the population, consisting of three to
172 four genotypes from each of the 25 families present in the population.
173 To select a subset of 190 genotypes from the HEB-25, we employed
174 the RAND() function available in Microsoft Excel version 2010 (MS-
175 Office). The use of this function allowed to randomly select three to
176 four lines from each of the 25 families, thus minimizing the potential
177 for bias in our selection process. To ensure that we selected an
178 extensively varied subset, we conducted a principal component
179 analysis (PCA) with R studio version 4.2.2. This analysis employed the
180 complete panel along with an SNP matrix consisting of 32,955
181 markers. Subsequently, the PCA plot was produced using the R-
182 package "ggplot2" (Wichham 2016) As depicted in Figure S1, our
183 dataset comprehensively represents the entire population and

184 exhibits considerable diversity. The selected subset was screened in
185 two subsequent experiment rounds (1st from November 2021 to
186 March 2022, 2nd from July to October 2022). A set of 12 genotypes
187 were included in both rounds of screening for normalization of the
188 experiments that was subsequently used to combine the data across
189 the two screening rounds via a linear mixed model, as outlined in the
190 “statistical analysis” section.

191 **Speed breeding experiments & phenotyping**

192 In order to fulfil the aim of this study, we gathered phenotypic data on
193 the development of barley plants under different controlled
194 environmental conditions. To achieve this, the experiments were
195 conducted in a glasshouse located at SRUC's Peter-Wilson campus
196 (55°55'17.386" N -3°10'42.175" E) manufactured by CambridgeHOK.
197 By measuring developmental traits of the plants under both
198 conditions, we aimed to gain insights into the genetic characteristics
199 of plant development under speed breeding.

200 The experimental conditions were meticulously chosen to ensure that
201 the phenotypic data collected accurately represented the impact of
202 the prolonged photoperiod used in speed breeding for cereals. The
203 first glasshouse compartment had a photoperiod of 16 hours of light
204 and 8 hours of darkness (16:8) (hereon called **Normal Breeding: NB**),
205 while the second compartment was set up for speed breeding and had
206 a photoperiod of 22 hours of light and 2 hours of darkness (22:2)

207 (hereon called **Speed Breeding: SB**). The temperature in both
208 compartments was programmed at 22 degrees Celsius during the day
209 and 17 degrees Celsius at night, in accordance with the specifications
210 of Watson et al., (2018). The experimental unit was one plant per 0.3
211 litres pot at a density of sowing of 77 plants/m², with five replicates
212 per genotype in a complete randomized block design (RBD). The plants
213 were distributed across the benches in 50 columns and 10 rows of
214 each treatment. The glasshouse is supplied with 400W High Pressure
215 Sodium light fixtures (Sylvania GroLux). The light intensity and the
216 temperature were measured via a quantum sensor (SKP 200 – Skye
217 Instruments) and dataloggers (EasyLog USB), respectively.

218 A set of 100 HEB lines were sown in November 2021, and another set
219 of 96 HEB lines in July 2022. Twelve HEB lines were cultivated under
220 both experiment rounds for normalization, as detailed in the statistical
221 analysis section.

222 Our study concentrated on two traits that have high heritability and
223 are essential for the successful completion of barley's life cycle and
224 development: days to heading (as a proxy for flowering time) and days
225 to maturity. We scored the traits by measuring the number of days it
226 took for the plant to reach growth stages BBCH49 (Heading - HEA) and
227 BBCH92 (Maturity – MAT) using the BBCH scale developed by
228 Lancashire et al., (1991) under both NB and SB conditions.
229 Additionally, we measured phenotypic plasticity, which is defined as

230 the changes exhibited by a genotype when grown in different
231 environments (Laitinen et al., 2019). Hence, in our study, plasticity is
232 the quantification of changes in developmental advancement of a
233 genotype across the two controlled environment conditions. Plasticity
234 was calculated for each genotype as the difference between the
235 average trait performances under NB and SB. We utilized these
236 derived traits to identify genetic factors that contribute to the
237 plasticity of HEA and MAT (Plasticity.HEA and Plasticity.MAT) across
238 NB and SB. This is a useful measure of adaptation, particularly in light
239 of the changing global environment characterized by abiotic stresses.
240 Gaining insights into the genetic basis of differential responses
241 observed in long days and very long days can help us understand how
242 plant development varies under different light conditions. This
243 understanding can be used to develop speed breeding protocols that
244 are tailored to specific genetic backgrounds or germplasm pools (e.g.,
245 elite versus wild).

246 **Statistical analyses**

247 After checking the phenotypic trait values manually for typographical
248 errors, we excluded outliers exceeding 3 standard deviations in each
249 genotype. Subsequently we removed genotypes with less than 3
250 replicates, per environment, from the analysis. Next, we fitted the
251 best linear mixed model to obtain the Best Linear Unbiased Estimator
252 (BLUE) for the studied traits, considering genotypes as fixed effects

253 and the experiment round, along with the row and column effects
254 (due to the varying light distribution across benches), as random
255 effect. Cultivating 12 common genotypes across experiment rounds
256 and incorporating this factor into the model enabled the
257 normalization of phenotypic data from both rounds of the
258 experiment. The models were fitted using “lmer” function from the
259 package “lme4” (Bates et al., 2015) in Rstudio version 4.2.2. We then
260 compared different models that considered either row and/or column
261 effects or none of them and selected the best performing model based
262 on the lower AIC (Akaike Information Criterion). The model
263 comparison was made via the “aic” function in the basic package
264 “stats” in Rstudio version 4.2.2.

265 Summing the genotypes effects to the intercept provided unique
266 values for each genotype which were then used for the GWAS and for
267 calculating plasticity.

268 Traits’ heritability was calculated using Piepho’s (Piepho and Möhring
269 2007) method using the R-scripts provided in Covarrubias-Pazaran
270 (2019).

271 The GWAS was performed using barley 50K SNP markers (Bayer et al.,
272 2017; Maurer and Pille 2019) by fitting following model:

$$273 \quad Y = Xb + Wm + Zu + e$$

274 where y is a $N \times 1$ column vector of the BLUE values of phenotypic data
275 of N NAM lines ($N = 190$ max in our case); b is a vector of population

276 structure effects as fixed effects; \mathbf{X} is an incidence matrix relating \mathbf{b} to
277 \mathbf{y} , consisting of principal components loadings from the PCA; \mathbf{m} is a
278 vector of fixed marker effects; \mathbf{W} is a marker matrix containing marker
279 types (as -1, 0 and 1); \mathbf{u} is a vector of random polygenic effects where
280 $\mathbf{u} \sim MVN(0, \mathbf{K}\sigma_u^2)$, \mathbf{K} is the additive relationship matrix obtained from the
281 markers using the function “A.mat” in the “rrBLUP” package
282 (Endelman 2011) in Rstudio version 4.2.2: \mathbf{Z} is an incidence matrix
283 linking \mathbf{u} to \mathbf{y} ; \mathbf{e} is a vector of random residuals where $\mathbf{e} \sim MVN(0, \mathbf{I}\sigma_e^2)$ and \mathbf{I}
284 is the identity matrix.

285 The correction for population structure was conducted via the kinship
286 correction and using the top 6 principal components as covariates,
287 namely the Q+K model (Isidro-Sánchez et al., 2017) . The number of
288 principal components used in the analysis was established from a
289 scree plot and by visually evaluating the component number at which
290 the rate of eigenvalue decrease began to plateau.

291 GWAS was conducted using SNP with MAF > 0.05 and the threshold of
292 False Discover Rate (type I error rate) was set at $\alpha = 0.05$ for each trait.
293 More details on the markers 50k Illumina Infinium iSelect SNP array
294 given in (Maurer and Pillen 2019).

295 In addition, markers effect size was computed using the “mixed.solve”
296 function in “rrBLUP” using Rstudio version version 4.2.2. The effects
297 are derived from the wild parents’ of the population.

298 **Analysis of alleles associated with *PPD-H1* and *ELF3***

299 Genotype groups were created from polymorphisms present at some
300 of the significantly associated markers in the two major QTLs (co-
301 located with the candidate genes *ELF3* and *PPD-H1*) found in the
302 GWAS scans. This yielded 4 different groups based on the allelic
303 combinations for the SNPs in the two loci. Being Barke the only
304 domesticated parent for the HEB-25 and used as reference genome
305 for the SNP computation, the alleles presenting polymorphism to this
306 genome are referred as “Hsp” (from *H. spontaneum*, wild parent) and
307 the Barke ones as “Hv” (from *H. vulgare*, domesticated parent) as in
308 Table 1. These four groups were then displayed via boxplot for all the
309 traits. A pairwise student t-tests was used for detecting differences
310 among the genotypic groups. All the comparisons between the groups
311 were made both in form of parametric t-test and permuted t-test. The
312 boxplots were created using the package “ggplot2” (Wickham 2016)
313 and t- tests via the “t.test” function in Rstudio version 4.2.2.

Group name	ELF3 allele	PPD-H1 allele
1	<i>Hv</i>	<i>Hv</i>
2	<i>Hsp</i>	<i>Hv</i>
3	<i>Hv</i>	<i>Hsp</i>
4	<i>Hsp</i>	<i>Hsp</i>

314

315 *Table 1. Genotypes groups based on the combinatorial allelic*
316 *combination from the haplotypic analysis. Hv: domesticated allele;*
317 *Hsp: wild allele. These haplotypes are derived from SNPs*
318 *underestimating original haplotypes harboured in the HEB25 families*
319 *as we do not have access to sequence information yet.*

320 **Results**

321 **Plant Development Acceleration due to Speed Breeding is Genotype**
322 **Dependent**

323 In general, plants completed their life cycles faster in SB than in NB.
324 Flowering (HEA) occurred 36 ± 7 days after germination in SB
325 conditions and 52 ± 11.5 days in NB conditions. This corresponds to a
326 15.9 ± 6.88 -day developmental acceleration under SB. However, the
327 average difference in days to maturity (MAT) between the two
328 conditions was 7.7 ± 6.88 days. **Figure S2** shows the distribution of
329 these traits as frequency histograms. BLUE values for HEA and MAT
330 and their derived plasticity traits, along with the summary statistics for

331 mean, standard deviation, minimum and maximum values, and
332 heritability values are provided in **Data S1 and Table S1**, respectively.

333 Notably, a significant proportion of the lines (approximately 90%)
334 flowered and matured earlier under SB than under NB. This suggests
335 that there is substantial variation in trait values and that SB has an
336 important effect on plant growth.

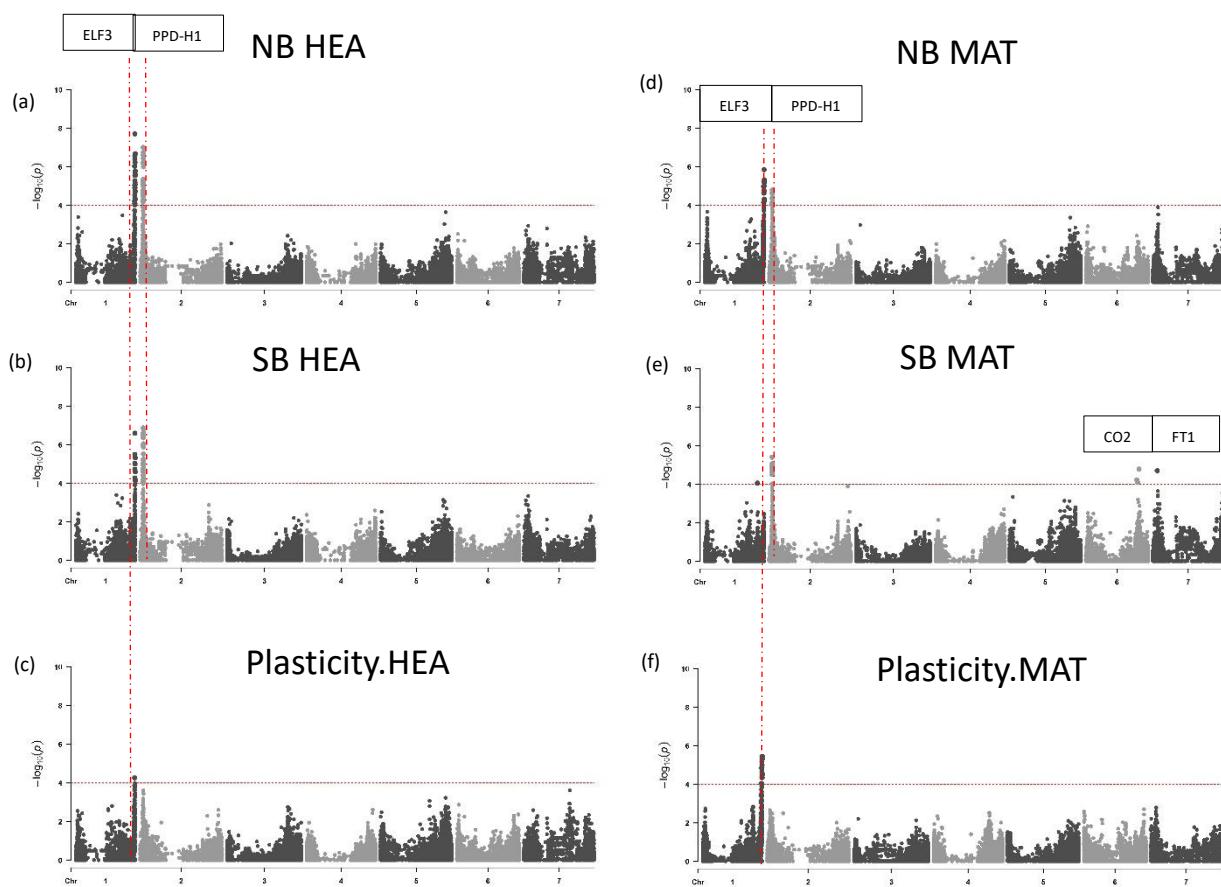
337 Plants subjected to SB exhibited a faster completion of their life cycles
338 compared to those under NB. This effect was evident under both
339 flowering and maturity stages. Importantly, a substantial amount of
340 genetic variability was observed in how plants responded to both
341 conditions, enabling a GWAS to be conducted as described in the
342 subsequent section. The heritability values of these traits were high,
343 albeit lower in SB than in NB (**Table S1**).

344 These findings indicate that certain genotypes display early flowering
345 only during prolonged photoperiods, whereas other are early
346 flowering under both long days and very long days, suggesting the
347 involvement of specific genes that regulate plant development.

348 **The effect of allele combinations associated with *ELF3* and *PPD-H1***
349 **on MAT, HEA, and Plasticity**

350 To better understand the genetic factors that control plant
351 development under SB and NB conditions, a GWAS was conducted for
352 each trait. We focused on identifying QTLs associated with the

353 regulation of the development under SB and NB conditions.
354 Specifically, six GWAS scans were performed across four primary
355 traits: HEA in NB, HEA in SB, MAT in NB, MAT in SB and their
356 corresponding plasticity traits: Plasticity.HEA and Plasticity.MAT,
357 across the two conditions. Manhattan plots and the list of markers,
358 their position, the level of association $-\log_{10}(P\text{-value}) \geq 4$ and their
359 effects are provided in **Figure 1** and **Data S2**, respectively.



360
361 *Figure 1. Manhattan plots from the six-trait (a-f). Seven barley*
362 *chromosomes are shown (1H-7H) horizontally and $-\log_{10}(p\text{-values})$*
363 *are displayed vertically by dotted line. Significant FDR threshold grey*
364 *dashed line set at 0.05. The coinciding flowering time candidate genes*

365 are shown in the rectangle boxes. Plots were created using the
366 “CMplot” package (Yin et al., 2021) in R studio version 4.2.2. The
367 details of the significant peaks and the markers underlying these peaks
368 are provided in **Data S2**.

369 The GWAS scans of HEA and MAT traits under both SB and NB revealed
370 two prominent QTLs that are co-located with the major flowering-
371 time genes *ELF3* on chromosome 1H and *PPD-H1* on chromosome 2H
372 (Russell et al., 2016), implicating their central importance in the
373 control of flowering and maturity. Interestingly the *PPD-H1*
374 association with MAT was maintained under both NB and SB.
375 Conversely, for the plasticity trait, the *ELF3* association remained
376 significant, highlighting its involvement in governing the plasticity of
377 HEA and MAT under SB conditions.

378 Our GWAS results emphasise the importance of major flowering-time
379 genes in barley for the regulation of HEA and MAT traits, which aligns
380 with previous studies (He et al., 2019; Maurer et al., 2015, 2016).
381 However, our findings also highlight the wider relevance of these two
382 genes specifically in the context of speed breeding, which has not
383 been previously reported in the literature. Furthermore, the
384 identification of two additional QTLs associated with the MAT trait in
385 speed breeding, located on chromosomes 7H and 6H in the regions of
386 *FLOWERING LOCUS T FT1* and *CONSTANS 2 CO2*, respectively,
387 indicated the potential involvement of additional genes in the control

388 of speed breeding. The detection of these QTLs in SB is particularly
389 interesting, considering the strong correlation observed between
390 MAT and HEA traits (**Figure S3, Table S2**). The presence of few
391 additional regions of relevance suggests that these specific regions
392 may have a greater influence on the MAT trait under SB, as they do
393 not exhibit significant association in NB. This finding implies the
394 existence a of unique genetic mechanisms that regulate MAT trait
395 responses in the context of speed breeding.

396 The validity of our findings was further supported through the
397 incorporation of major QTL peaks from chromosome 1H and 2H as
398 covariates in our GWAS model (**Figure S4, Data S5**). As expected, these
399 two major QTLs disappeared after incorporation as covariates.
400 Consequently, we successfully detected a prominent QTL peak
401 proximal to the *FT1* genomic region on chromosome 7H, indicating a
402 significant association with both HEA and MAT traits. Additionally, we
403 observed smaller QTL peaks in other regions such as chromosome 1H
404 (MAT in SB, candidate genes *PPD-H2* and *GA20ox*) and 5H (HEA in NB,
405 candidate gene *CO2*).

406 The conspicuous association detected near the *FT1* genomic region on
407 chromosome 7H strongly suggests its importance in regulating HEA
408 and MAT traits in addition to *PPD-H1* and *ELF3*. Furthermore, the
409 significant association of markers in regions other than the ones
410 containing the two main QTLs identified, implies the involvement of

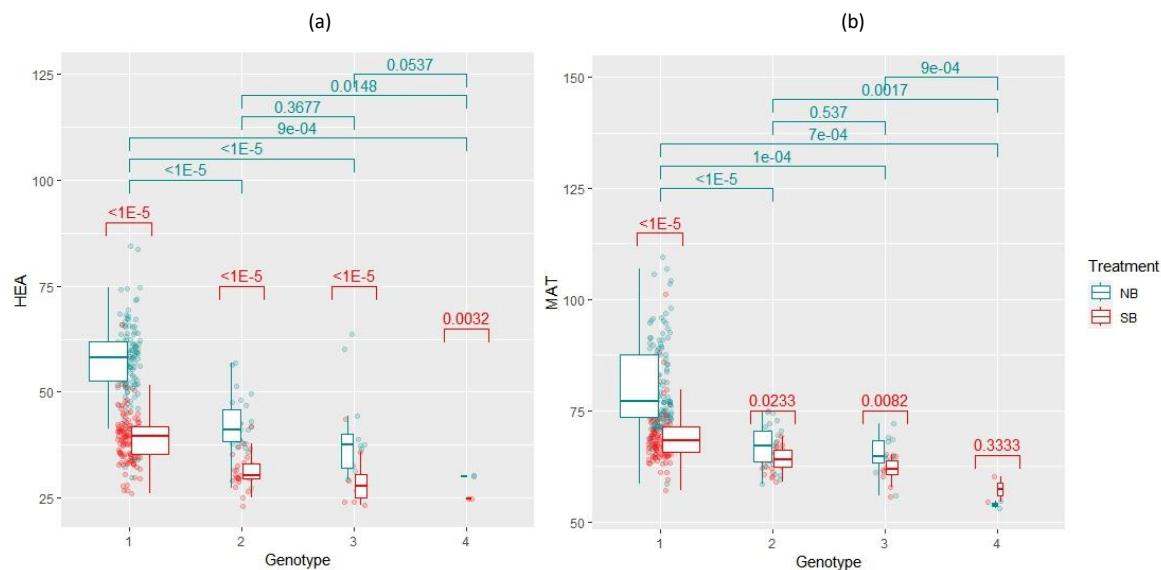
411 the additional genes *PPD-H2*, *GA20ox* and *CO2* in the regulation of
412 these traits.

413 Overall, our GWAS results shed light on the crucial role of major
414 flowering-time genes in controlling HEA and MAT traits in barley.
415 Additionally, they reveal the broader significance of these genes in the
416 specific context of speed breeding, providing valuable insights not
417 previously reported in the literature. The identification of QTLs
418 associated with the MAT trait in SB further suggests the involvement
419 of additional genes, highlighting the complexity of this trait and its
420 response to different growth conditions. In fact, it is important to
421 mention that the effect of hand watering on MAT is more prominent
422 than its effect on HEA (Qaseem et al., 2019).

423 **Domesticated Alleles at *ELF3* and *PPD-H1* Confer Higher Plasticity**

424 The combination of alleles at the *ELF3* and *PPD-H1* genes are
425 important under both SB and NB conditions. Different allelic
426 combinations at *ELF3* and *PPD-H1* loci (**Table 1**, *PPD-H1Hv/ELF3Hv* -
427 group 1, *PPD-H1Hv/ELF3Hsp* - group 2, *PPD-H1Hsp/ELF3Hv* - group 3,
428 *PPD-H1Hsp/ELF3Hsp* - group 4) also affect MAT, HEA and their
429 plasticity. As observed by Maurer et al., (2015) and Zahn et al., (2023),
430 genotypes carrying at least one wild allele at one of the two loci
431 (groups 2,3 and 4) tend to flower earlier compared with lines carrying
432 domesticated alleles under both loci (group 1, p. values <=0.0009,

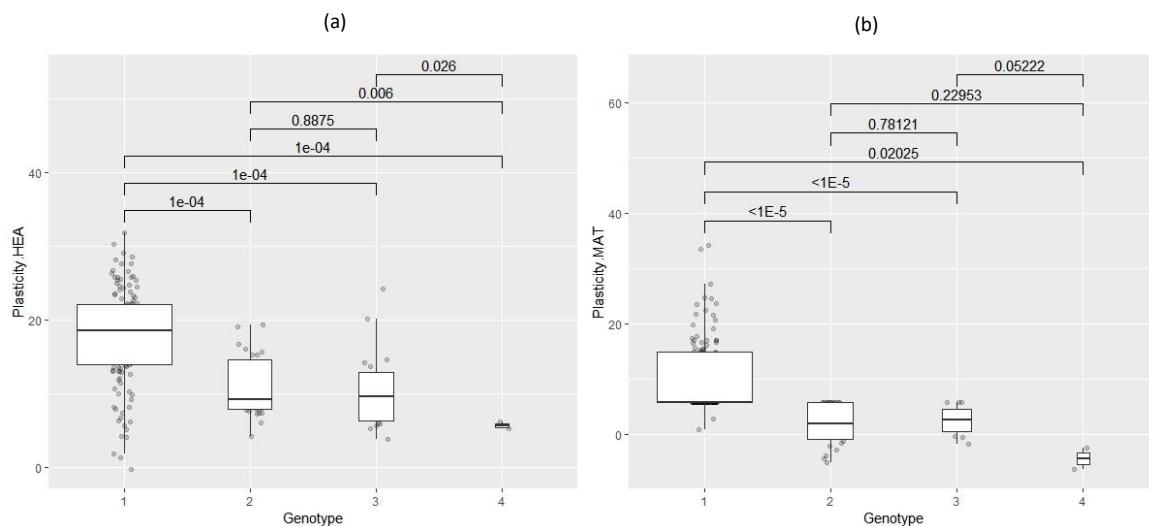
433 **Figure 2).** This is consistent with the wild alleles effect of the
434 significant markers found in our GWAS scan, as their effect is negative
435 on the traits value, accelerating the plant's development (**Data S2**).



436
437 *Figure 2. PPD-H1 and ELF3 alleles-based box plots from HEA (a) and*
438 *MAT (b). Boxplots of the response of different genotype groups to MAT*
439 *and HEA, arising from the combinatorial allelic analysis. PPD-*
440 *H1_{Hv}/ELF3_{Hv} - group 1, PPD-H1_{Hv}/ELF3_{Hsp} - group 2, PPD-H1_{Hsp}/ELF3_{Hv} -*
441 *group 3, PPD-H1_{Hsp}/ELF3_{Hsp} - group 4. P-values shown are from*
442 *permutation t-tests.*

443 Domesticated haplotypes at both loci appear to give higher levels of
444 plasticity compared to the wild haplotypes (p.values<=0.02, **Figure 3**,
445 **Data S3a**). Nevertheless, the means between experimental conditions
446 within all genotypes' groups are significantly different except for
447 genotype group 4's MAT. Therefore, SB reduced the HEA and MAT in
448 all the genotypes studied, however, looking at the means in **Data S3b**
449 and **Figure 3**, the extent of cycling acceleration in genotypes carrying

450 wild alleles is very low compared to the ones harbouring domesticated
451 alleles, especially for MAT. Hence, wild alleles at *PPD-H1* and *ELF3*
452 confer early flowering under both conditions.



453
454 *Figure 3. PPD-H1 and ELF3 alleles-based box plots from Plasticity. HEA*
455 *(a) and Plasticity.MAT (b). Boxplots of the response of different*
456 *genotype groups to Plasticity. HEA and Plasticity., arising from the*
457 *combinatorial allelic analysis. PPD-H1_{Hv}/ELF3_{Hv} - group 1, PPD-*
458 *H1_{Hv}/ELF3_{Hsp} - group 2, PPD-H1_{Hsp}/ELF3_{Hv} - group 3, PPD-H1_{Hsp}/ELF3_{Hsp} -*
459 *group 4. Significance shown are from permutation t-tests.*

460 Finally, we ranked the genotypes based on the MAT value under SB
461 and examined the genotype group to which the latest maturing
462 genotypes belonged. This analysis is valuable in investigating whether
463 breeders tend to unintentionally select for specific alleles at *PPD-H1*
464 and *ELF3* if they do not advance the latest maturing plants group in
465 the population. Later maturing plants in the 75th percentile harboured
466 domesticated alleles at *ELF3* and *PPD-H1* genes (**Data S5, Figure S5**).

467 Discussion

468 To our knowledge this is the first time that the underpinning genetic
469 control of speed breeding has been explored. Various studies have
470 described the benefits of speed breeding (Ahmar et al., 2020; Bhatta
471 et al., 2021; Bohra et al., 2020; Pandey et al., 2022; Samantara et al.,
472 2022; Song et al., 2022; Wanga et al., 2021) and optimised protocols
473 for the deployment of speed breeding (Cazzola et al., 2020; Chiurugwi
474 et al., 2019; Fang et al., 2021; Watson et al., 2018; J. M. Hickey et al.,
475 2017; Mobini et al., 2020; Samineni et al., 2020; Schilling et al., 2023)
476 but the genetic basis of plant development under such conditions
477 remains unexplored. In this study we adopted a GWAS approach to
478 unravel the genetic control of speed breeding in a barley NAM
479 population grown under two growth conditions, one with a
480 photoperiod of 22 hours of light 2 hours of darkness (SB) and the other
481 on 16 hours of light and 8 hours of darkness (NB). By studying a subset
482 of the spring barley HEB 25 NAM population (Maurer et al., 2015) a
483 broad range of wild and domesticated alleles were explored and led
484 to the identification of candidate genes associated with the control of
485 developmental traits under both SB and NB. Two significant candidate
486 genes were pinpointed: *ELF3* and *PPD-H1* controlling both days to
487 heading and days to maturity. Most importantly, by measuring the
488 changes exhibited by an individual genotype over the two treatments
489 we were able to derive an estimate for plasticity and ascribe a

490 candidate gene *ELF3* that is strongly associated with it, supporting its
491 role as a key hub integrating gene networks influencing overall
492 plasticity (Laitinen et al., 2019).

493 Previous studies have shown that the *PPD-H1* and *ELF3* genes are
494 involved in the genetic control of several agronomic traits in barley
495 (Digel et al., 2016; Ejaz and von Korff 2017; Gol et al., 2021; Ochagavía
496 et al., 2022). At the *PPD-H1* locus, a variety of natural variants have
497 been identified, and categorized into two distinct groups: the sensitive
498 allele, *Ppd-H1* which reduces flowering time during long days and the
499 insensitive variant, *ppd-H1* which delays flowering in long days
500 (Russell et al., 2016; Turner et al., 2005; Fernández-Calleja et al.,
501 2021). The former variant likely represents the ancestral allele, found
502 in HEB-25 and present in winter and Australian barleys (Hu et al.,
503 2023) whereas the *ppd-H1* allele is prevalent in Barke and numerous
504 European and North American spring barley cultivars. With respect to
505 *ELF3*, knowledge and understanding of the phenotypic effects of the
506 allelic series is less established than for *PPD-H1*. Faure et al., (2012)
507 were the first to discover a loss of function allele at this locus and they
508 identified *ELF3* as the candidate gene responsible for the *eam8*
509 mutant originating from the Scandinavian induced mutation
510 experiments performed in the past century (Lundqvist 2009). This
511 allele confers early flowering both in short and long days, compared
512 to the domesticated allele. Such response it is similar to the one

513 observed in our study by wild alleles in the HEB 25 that aligns with the
514 findings from Zahn et al., (2023) and Zhu et al., (2023).

515 Both *PPD-H1* and *ELF3* are linked to the expression of *FT1* and *GA20ox*
516 genes that are downstream floral integrators that control the
517 flowering response (Boden et al., 2014; Campoli et al., 2012; Cheng et
518 al., 2023; Faure et al., 2012; Turner et al., 2005). *ELF3* delays the
519 flowering response whereas *PPD-H1* accelerates the response in long
520 days. In *Arabidopsis*, *ELF3* is a repressor of *PRR7* (Dixon et al., 2011;
521 Herrero et al., 2012; Nusinow et al., 2011), which is an homologue of
522 *PPD-H1*. In barley, this interaction has been studied at the transcript
523 level (Faure et al., 2012; Zahn et al., 2023) with both the allele present
524 in *eam8* mutant and the wild *ELF3hsp* correlate with a higher *PPD-H1*
525 expression that leads to early flowering compared to the
526 domesticated *ELF3hv* variant. Furthermore, Müller et al., (2020)
527 hypothesized that, as seen in *Arabidopsis*, *ELF3* antagonizes the light
528 input in the circadian clock during the night. Such response would
529 explain why the domesticated *ELF3hv* alleles, under NB, confer late
530 flowering, however, under SB such genotypes accelerate plant
531 development more significantly compared to genotypes that harbour
532 wild alleles, as in the latter conditions the night is very short. However,
533 such response it is visible only in a *ppd-H1* background as *Ppd-H1*
534 confers early flowering under both conditions. In this context the
535 sensitive allele *Ppd-H1* under long days seems to be less influenced by

536 *ELF3*'s suppression. In addition, an independent pathway has been
537 hypothesized where the allele behind *eam8* and the wild *ELF3hsp*
538 allele induce early flowering independently from *Ppd-H1* (Boden et al.,
539 2014; Faure et al., 2012; Zahn et al., 2023). This would explain why we
540 observe early flowering phenotypes in the presence of *ELF3hsp* in a
541 *ppd-H1* background.

542 In summary, this study has highlighted the importance of both *PPD-*
543 *H1* and *ELF3* in the control of speed breeding in barley. The
544 deployment of the HEB-25 population enabled alleles at these two loci
545 to be fully explored in the context of speed breeding. Our findings will
546 be particularly important for the deployment of SB in crop
547 improvement programs that focus on the incorporation of new
548 sources of genetic variation from wild relatives (Gramazio et al., 2021;
549 Hao et al., 2020; Hernandez et al., 2020; Khan et al., 2023; Zhang et
550 al., 2023). Data from this study predict that the deployment of this
551 technology to accelerate generation time in breeding, will select
552 against specific alleles in the genomic regions on chromosomes 1 and
553 2 where *PPD-H1* and *ELF3* are located, if late flowering genotypes will
554 not be advanced to the next generation. Furthermore, a comparison
555 of the allelic series at *PPD-H1* and *ELF3* (**Figure 3**) identified that
556 domesticated alleles at these two loci, which are those that tend to be
557 unintentionally selected against under rapid cycling conditions, also
558 are likely to be associated with higher levels of plasticity that may

559 guide and support their deployment in breeding programs designed
560 to create climate resilient cultivars. Finally, genotypes that harbour
561 wild alleles showed early flowering under both conditions, suggesting
562 that, in such genotypes, speed breeding might not be as important to
563 accelerate generation time as in domesticated genotypes.

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572 **Supplementary Data**

573 **Figure S1.** Principal component analysis for HEB-25 based on 32,955
574 SNP data.

575 **Figure S2.** Figure showing the frequency distribution of the 6 traits (a-
576 f).

577 **Figure S3.** The plot displays a correlation matrix (from Table S2), with
578 the six different traits represented along both the x-axis and the y-axis.

579 **Figure S4.** Manhattan plots from the six-trait using PPD-H1 and ELF3
580 as covariates.

581 **Figure S5.** The graph displays a distribution of a MAT SB across 162
582 entries, categorized into four distinct genotype groups. The x-axis
583 represents percentiles. Each point is color-coded to represent one of
584 the four genotype groups, allowing for a visual comparison of their
585 distribution in the dataset.

586 **Data S1.** List of the BLUEs value of each of the 6 traits for the
587 genotypes of the HEB 25 used in this study.

588 **Data S2** Significant ($\log_{10} p\text{-val} > 4$) markers and their effect for the 6
589 GWAS for each of the trait analyzed

590 **Data S3a.** P-values resulted observed and permuted based data t-
591 tests between genotype groups.

592 **Data S3b.** Summary statistics of the different genotype groups as in
593 **Table 1.**

594 **Data S4.** List in decrescent order the genotypes and the genotype
595 groups for the trait MAT SB.

596 **Data S5.** Significant ($\log_{10} p\text{-val} > 4$) markers and their effect for the
597 6 GWAS, using ELF3 and PPD-H1 as covariates, for each of the trait
598 analyzed.

599 **Table S1** Table showing the summary statistics of the 4 traits with
600 mean, standard deviation, minimum, maximum and heritability
601 estimates using Piepho's method

602 **Table S2** Table showing Pearson correlation matrix between the 6
603 different traits.

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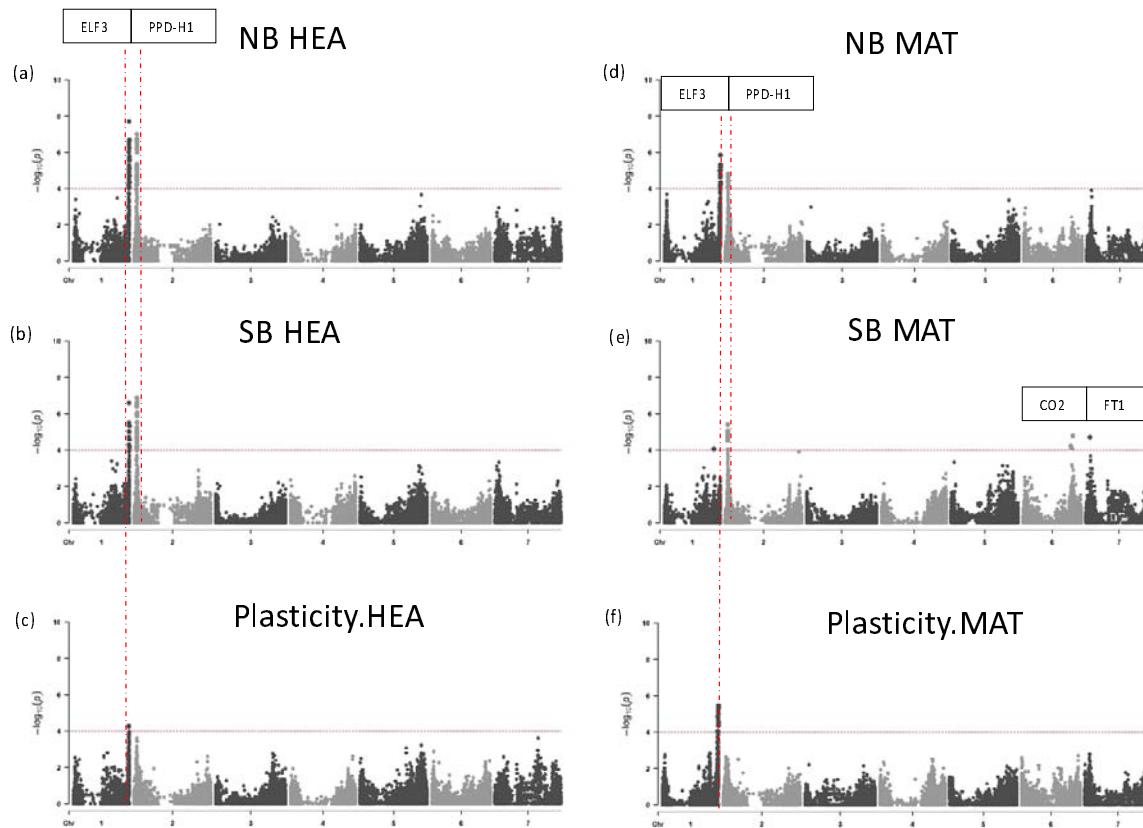
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Group name	ELF3 allele	PPD-H1 allele
1	<i>Hv</i>	<i>Hv</i>
2	<i>Hsp</i>	<i>Hv</i>
3	<i>Hv</i>	<i>Hsp</i>
4	<i>Hsp</i>	<i>Hsp</i>

Table 1. Genotypes groups based on the combinatorial allelic combination from the haplotypic analysis. *Hv*: domesticated allele; *Hsp*: wild allele. These haplotypes are derived from SNPs underestimating original haplotypes harboured in the HEB25 families as we do not have access to sequence information yet.



*Figure 1. Manhattan plots from the six-trait (a-f). Seven barley chromosomes are shown (1H-7H) horizontally and $-\log_{10}(p\text{-values})$ are displayed vertically by dotted line. Significant FDR threshold grey dashed line set at 0.05. The coinciding flowering time candidate genes are shown in the rectangle boxes. Plots were created using the “CMplot” package (Yin et al., 2021) in R studio version 4.2.2. The details of the significant peaks and the markers underlying these peaks are provided in **Data S2**.*

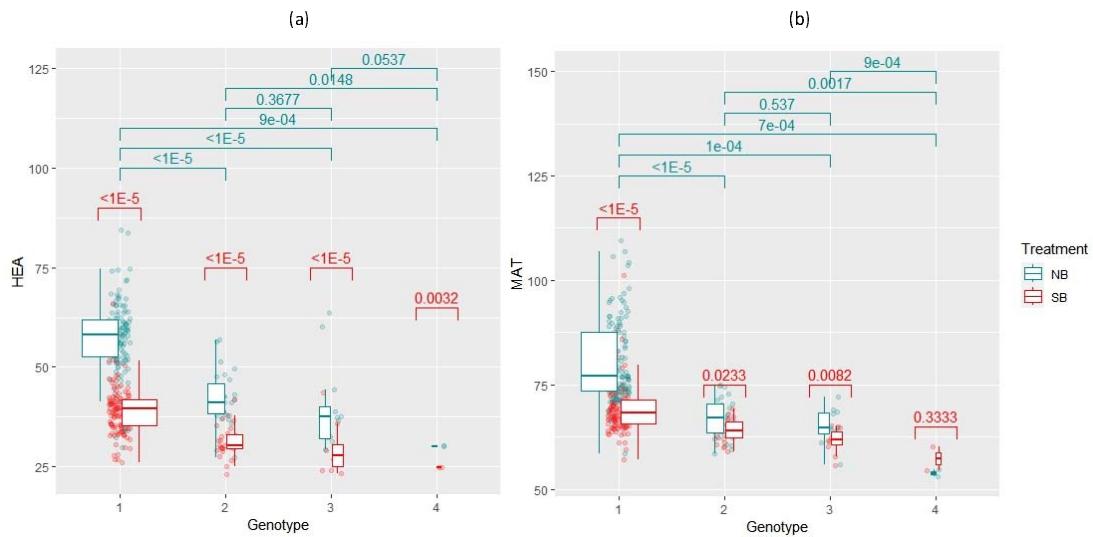


Figure 2. PPD-H1 and ELF3 alleles-based box plots from HEA (a) and MAT (b). Boxplots of the response of different genotype groups to MAT and HEA, arising from the combinatorial allelic analysis. PPD-H1_{Hv}/ELF3_{Hv} - group 1, PPD-H1_{Hv}/ELF3_{Hsp} - group 2, PPD-H1_{Hsp}/ELF3_{Hv} - group 3, PPD-H1_{Hsp}/ELF3_{Hsp} - group 4. P-values shown are from permutation t-tests.

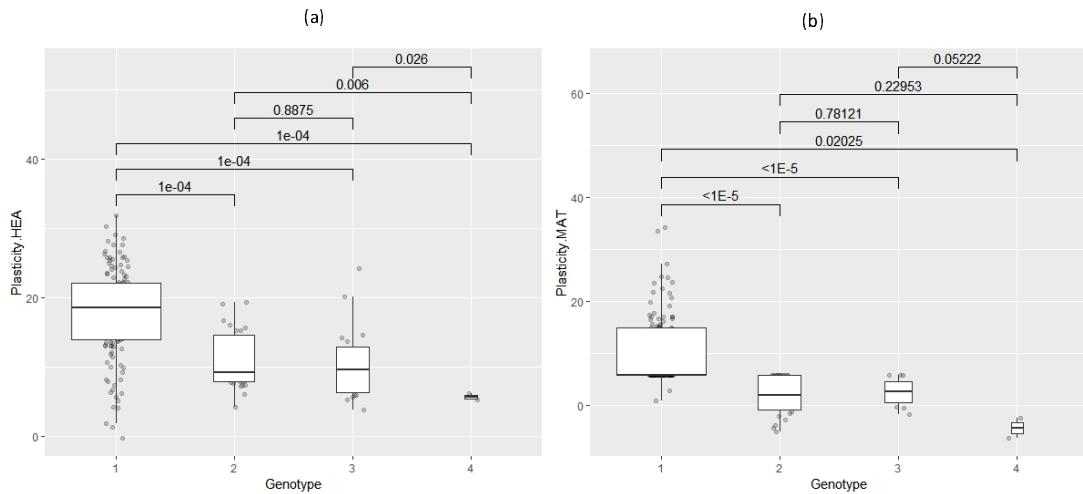


Figure 3. PPD-H1 and ELF3 alleles-based box plots from Plasticity. HEA (a) and Plasticity.MAT (b). Boxplots of the response of different genotype groups to Plasticity. HEA and Plasticity., arising from the combinatorial allelic analysis. PPD-H1_{Hv}/ELF3_{Hv} - group 1, PPD-H1_{Hv}/ELF3_{Hsp} - group 2, PPD-H1_{Hsp}/ELF3_{Hv} - group 3, PPD-H1_{Hsp}/ELF3_{Hsp}- group 4. Significance shown are from permutation t-tests.