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This is the final peer-reviewed author's accepted manuscript (postprint) of the following publication:

*Published Version:*

A generalized phenological model for durum wheat: application to the Italian peninsula / Di Paola, Arianna; Ventura, Francesca; Vignudelli, Marco; Bombelli, Antonio; Severini, Maurizio. - In: JOURNAL OF THE SCIENCE OF FOOD AND AGRICULTURE. - ISSN 0022-5142. - ELETTRONICO. - 100:11(2020), pp. 4093-4100. [10.1002/jsfa.9864]

This version is available at: <https://hdl.handle.net/11585/692769> since: 2019-07-24

*Published:*

DOI: <http://doi.org/10.1002/jsfa.9864>

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# A generalised phenological model for durum wheat. Application to the Italian peninsula.

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## ABSTRACT

**BACKGROUND:** A likely increasing demand for varieties mixtures, landraces and genetic diversity in cropping systems will underpin calls for models able to generalise phenological development at the species level, while providing the expected range of phenological variability. In the present article, we aimed to obtain a generalised phenological model of durum wheat (*Triticum durum*, Desf.).

**RESULTS:** By using a large phenological dataset embracing field data collected under different sowing dates, varieties, and locations over the Italian peninsula, we searched for the phenophases enabling the best linear approximations between developmental rates and air temperature, in order to minimize the residual variability from drivers other than temperature, as genetic and environmental diversity. The developmental rates of the resulting phases were then examined with respect to the mean daylength, to determine possible additional relations with photoperiod. If a correlation with daylength was also present, the developmental rate is calibrated by multiple linear regression, otherwise by simple linear regression of temperature. The resulting calibration, tested on an independent data subset, proves that the model is able to generalise wheat development over the Italian peninsula with high accuracy (MAE =3-8 days;  $R^2= 0.75-0.98$ ), regardless of the wheat variety.

**CONCLUSION:** The generalised phenological model is potentially suitable for many agro-ecological and large-scale applications. It is hoped that the model will aid situations where phenological observations to parameterize a model are still lacking, as is probably the case for landraces and underutilized crop varieties.

**Keywords:** *durum wheat*, phenological model, developmental rates, agro-ecology, landraces

## 1. Introduction

The way the plants progress through their life cycle (i.e. their phenology) represents one of the most important plant/environment adaptation strategy [1,2]. Phenological models are essential tools for organic farming, and other types of crop management, as they allow for scheduling crop practices and irrigation [3]. Moreover, such models can help practices aimed at reducing climate risks and

38 optimizing external resources, and enhancing pest and weed [4,5,6]. However, contemporary  
39 modelling tools, of which the phenological module represents a key component, are typically  
40 designed for optimising the productivity of monoculture at the field scale [7]. Phenological models  
41 for crop mixtures, large-scale simulations and, overall, for situations where no data are available, as  
42 may happen for landraces (locally adapted varieties) and underutilized varieties remain absent in  
43 literature.

44  
45 Of the well-established predictor variables for wheat development, namely temperature,  
46 vernalization and photoperiod [2,8,9,10,11], temperature is considered the most important [2,8].

47 Vernalization is the physiological mechanism that plants use to compensate for winter season and to  
48 flower in spring [12,13]. Wheat cultivars requiring vernalization become sensible to photoperiod  
49 after prolonged exposure to cold temperature, although the amount of cold requirement in the field  
50 is still uncertain [14,15]. Plants sensitive to photoperiod grow faster under increasing daylength  
51 [16].

52 A versatile way to model plant development is to regress its rate (the reciprocal of the time to  
53 mature a given phase,  $d^{-1}$ ) against the mean value(s) of the predictor variable(s) experienced during  
54 that phase [17]. Here we refer to the resulting equation, whether linear or not, as the Developmental  
55 Rate (DR) function.

56 In the present work, we aimed to obtain a generalised phenological model for durum wheat, valid  
57 over the Italian peninsula. By *generalised*, we mean a model that could be used to simulate any  
58 wheat variety, climate and agricultural regimes. Such a model would allow reliable applications  
59 over numerous case studies, such as those involving landraces and underutilized crop varieties,  
60 cultivar mixtures used in agro-ecology to increase the resilience of the field [18], and large-scale  
61 simulations of phenological development.

62 The development of a generalised model implies the use of field observations representative of a  
63 wide range of environmental, climatic and genotypic variability. It also requires an approach that  
64 minimizes the variability in the developmental rates due to such heterogeneity. To treat with this,  
65 we used a large phenological database on durum wheat embracing data collected from diverse  
66 years, varieties, sowing dates, and experimental sites across the Italian peninsula to identify the  
67 wheat phases with developmental rates better approximated to a linear function of the primary  
68 driver (i.e. temperature). After suitable phases were identified, we also examined the developmental  
69 rates with respect to the mean daylength, searching for an additional explanatory power from the  
70 photoperiod. In the phases where a correlation with daylength also emerged, we estimated  
71 developmental rate functions by multiple linear regression with respect to both temperature and  
72 photoperiod, otherwise by simple linear regression of temperature.

## 73 **2 Methods**

74 We opted for linear functions as the related errors are constant, allowing for a robust estimate of  
75 critical values of temperature. However, the same approach could be followed also using non-linear  
76 functions. The underlying principle of our approach is that developmental rate functions may  
77 change (being linear or not) among phases [19]. Thus, by inspecting many phases it is possible to  
78 find out those where the best linear temperature responses hold, if any, and, in turns, where the

79 residual variability in the developmental rates explainable by variables other than temperature, as  
80 environmental[2] and genotypic[20] diversity, is minimal.

### 81 **2.1 Developmental Rate functions of Temperature (T) and Photoperiod (P)**

82 The developmental rate of a given phase could be described, in the first instance, as a linear  
83 function of temperature, as early suggested by [2,21,22]:

$$84 \quad DR[T] = a + bT \quad (1)$$

85 where

- 86 -  $DR$  is the developmental rate, i.e. the reciprocal of the time to mature the phase [ $d^{-1}$ ];
- 87 -  $T$  is the mean air temperature experienced during the phase [ $^{\circ}C$ ];
- 88 -  $a$  is the intercept [ $d^{-1}$ ] and  $b$  is the slope [ $^{\circ}C^{-1}d^{-1}$ ] of the linear function, respectively.

89 The intersection of the linear DR function with the abscissa returns the value for the base  
90 temperature  $T_0[^{\circ}C]$  [20,21]:

$$91 \quad T_0 = -a/b \quad (2)$$

92

93  $T_0$  represents the critical temperature below which plant development is assumed nil, since the DR  
94 would assume negative values.

95 In the same way, following the approach adopted by [17], we suggest that whenever an additional  
96 linear relation between developmental rates and daylength holds, a multiple linear regression can be  
97 considered as:

$$98 \quad DR[T, P] = a + bT + cP \quad (3)$$

99 where

- 100 -  $P$  is the mean daylength during the phase in hours [hr];
- 101 -  $a$ ,  $b$  and  $c$  the coefficients of the multiple regression.

102 Formally, even in case of multiple linear regression, the development rate stops when temperature  
103 and photoperiod fall below critical values. We name these critical values as  $T_{0m}$  and  $P_{0m}$  in analogy  
104 with the symbol used for base temperature, where the subscript  $m$  stands for “multiple”. Similarly,  
105 the values of  $T_{0m}$  and  $P_{0m}$  are formally given by the intersection of the linear DR function (projected  
106 on a two-dimensional scatter plot) with the corresponding abscissa.

107 Using phenological observations, i.e. a phase time length and the related mean air temperature and  
108 daylength experienced during that phase, it is possible to ascertain whether the development rate is  
109 a linear function of mean temperature, or temperature and daylength, and if so, perform a least  
110 squares regression to estimate the parameters of Eq. (1) or (3), respectively.

### 111 **2.2 Using DRs to simulate wheat development**

112 When only the temperature is the explanatory variable, the prediction of a given phenological event,  
113 i.e. the number of days to complete a phase, could be achieved with the only inputs of sowing date  
114 and daily mean air temperatures as follow:

$$115 \sum_{j=1}^S DR_j[T_j] = 1 \quad (4)$$

116 Where  $DR_j$  is the daily developmental rate of the phase,  $S$  is the phase duration in days and  $T_j$  is the  
117 mean air temperature [ $^{\circ}\text{C}$ ] of the  $j$ -day. The linear behaviour of the phase is analytically expressed  
118 as;

$$119 DR_j = a + bT_j \quad (\text{if } T_j > T_0) \quad (5)$$

$$120 DR_j = 0 \quad (\text{if } T_j \leq T_0) \quad (6)$$

121 When the sum of the daily rates reaches 1, the end of the phase  $S$  is achieved [17]. The starting date  
122 ( $j=1$ ) of the next phenological phase is on the day following the end of the current, except the last  
123 phase which defines the end of the annual crop life cycle.

124 Similarly, when both temperature and daylength are explanatory variables,  $S$  can be obtained as:

$$125 \sum_{j=1}^S DR_j[T_j, P_j] = 1 \quad (7)$$

126 Where

$$127 DR_j = a + bT_j + cP_j \quad (\text{if } T_j > T_{0m} \text{ and } P_j > P_{0m}) \quad (8)$$

$$128 DR_j = 0 \quad (\text{if } T_j < T_{0m} \text{ and } P_j < P_{0m}) \quad (9)$$

129 and  $P_j$  is the daily mean daylength [hr] of the  $j$ -day.

### 130 **2.3 Data source**

131 In this work, phenological field observations were retrieved from the PHEANGRI database  
132 (<http://phenagri.entecra.it/>) and the Agrophenological Station of Cadriano (University of Bologna,  
133 DISTAL, Italy).

134 PHENAGRI provides a free database of field observations on both weather and crop phenological  
135 development, collected from several experimental sites widely spread over Italy, during the period  
136 1996-1999. Weather data provided records from *in situ* meteorological stations (when present) or  
137 from the nearest reference station to the experimental field. Reference stations were those belonging  
138 to the national networks of the Italian Council for Agricultural Research and Analysis of  
139 Agricultural Economics (CREA) or to the Air Force Met service (AFM).

140 Available observations on durum wheat included dates of several phenological events obtained  
141 from the scalar sowing dates (ranging from the beginning of November to the beginning of March),  
142 several varieties, and five experimental sites placed in: S. Angelo Lodigiano (LO) and Garica di  
143 Podenzano (PC), northern Italy; Vasto (CH) and Foggia (FG), south-central Italy; Cassibile (SR),  
144 southern Italy (Fig. 1). Further details on the experimental sites and reference meteorological  
145 stations are available at the PHEANGRI project website (<http://phenagri.entecra.it/>).

146 Observed wheat phenological events, in BBCH centesimal scale [23] were: sowing (BBCH 00),  
147 emergence (BBCH 09), three leaves unfolded (BBCH 13-14), beginning of stem elongation (BBCH  
148 30), second node detectable (BBCH 32), beginning of booting (BBCH 41), beginning/end of  
149 heading (BBCH 51/59), beginning/end of anthesis (BBCH 61/69), milk maturity (BBCH 73-77),  
150 and physiological maturity (BBCH 89). The dates of each phenological event refer to the median  
151 date between the sampled plants (at least ten per variety). Further details on the operational protocol  
152 of the PHENAGRI project are reported in [24].

153 The Agrophenological Station of Cadriano (BO) is an experimental site led by the University of  
154 Bologna, collecting data from 2003 to the present, following the same operational protocol of  
155 PHENAGRI. Observations enclosed the same phenological events reported above, obtained from  
156 autumn sowing dates (October-November), for durum wheat cv. Duilio. Weather data were  
157 retrieved from *in situ* agrometeorological station. Details on both the agro-phenological and agro-  
158 meteorological station of Cadriano are available in [25,26,27].

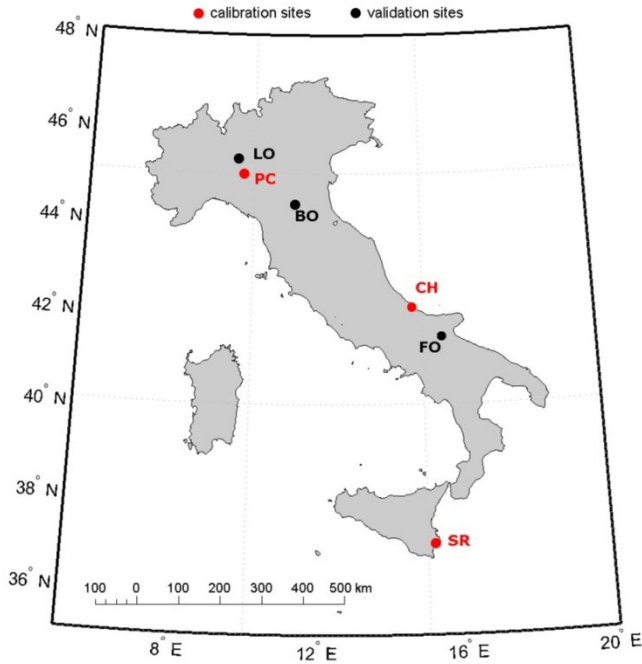
159 Further available data from the Experimental Farm of Cadriano, collected in the period 1972-1978,  
160 were also used (shared by personal communication). Observed events, which correspond to BBCH  
161 values, were: beginning of stem elongation (BBCH 30), beginning of heading (BBCH 51) and  
162 physiological maturity (BBCH 89).

## 163 **2.4 Data analysis**

164 We defined two subsets of data, namely:

- 165 - *Calibration dataset*: Data on durum wheat varieties Creso and Simeto, obtained from the  
166 PHENAGRI experimental sites of Garica di Podenzano (PC), Vasto (CH) and Cassibile (SR).
- 167 - *Validation dataset*: observations on durum wheat varieties Ares, Cirillo, Colosseo, and  
168 Zenit, obtained from the PHENAGRI experimental sites of S. Angelo Lodigiano (LO) and Foggia  
169 (FG); observations on varieties Duilio (collected during 2003-2016), and Sansone and Valgerardo  
170 (collected during 1972-1978), from the experimental farm of Cadriano (BO).

171 Figure 1 shows the geographical distribution of the calibration and validation sites.



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**Figure 1.** Geographical distribution of the experimental sites. Red dots: experimental sites whose data were used to calibrate the phenological model (*calibration sites*). Black dots: experimental sites whose data were used to test the model performances (*validation sites*).

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From the calibration dataset, we estimated the developmental rate of many phenophases and related mean air temperature experienced during each phase. Among suitable combinations to define the whole wheat life cycle, we empirically identified the wheat phases where the relationships between developmental rates and mean air temperature were better approximated to a linear function ( $p$ -values  $< 0.01$ ). This selection was achieved by looking at the Pearson linear correlation ( $r$ ) coefficients. Then, we checked for further correlations with daylength. Mean daylength was computed according to the FAO guideline [28] on a daily basis and then averaged over the phase time length. If a further correlation with daylength held, and in the case of no collinearity between temperature and daylength, DR functions were regressed using ordinary least squares technique in the form of Eq. (3), otherwise in the form of Eq. (1). For each phase we provided *i*) the Pearson correlation coefficient ( $r$ ); *ii*) the coefficients of the linear functions and the critical values for temperature and daylength (if any); *iii*) the residuals to check that the correlations are unbiased and homoskedastic; *iv*) the error variable ( $\epsilon$ ).

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The coefficients estimated for each DR function were used to simulate wheat development at the validation sites, according to eq. (7) or (4) depending on whether the developmental rates are also correlated to photoperiod or not, respectively.

192  
193

Results were compared with the observations (*validation set*) looking at the Mean Absolute Errors (MAE, [d]), normalised MAE (NMAE, [%]) and the model efficiency (EF, dimensionless).

194

The statistical indices are defined as:

195

$$MAE = \frac{\sum_{i=1}^n (|S_i - O_i|)}{n} \quad (11)$$

196 
$$NMAE = \frac{MAE}{\bar{O}} \quad (12)$$

197 
$$EF = 1 - \frac{\sum_{i=1}^n (S_i - O_i)^2}{\sum_{i=1}^n (O_i - \bar{O})^2} \quad (13)$$

198

199 Where  $S_i$  and  $O_i$  are the days after sowing of the  $i^{\text{th}}$  prediction and observation, respectively,  $n$  the  
 200 number of observations and  $\bar{O}$  is the mean observation from the whole dataset.

201 MAE [29] indicates the mean absolute values of errors (predictions minus observations) in absolute  
 202 terms. The lower the values of MAE, the higher the agreement of the model prediction with the  
 203 observations. NMAE expresses the MAE with respect to the observed phase length, which permits  
 204 the expression of errors in relative terms. Generally, simulations are considered excellent when  
 205 relative errors are less than 10%, good when ranging from 10 and 20%, fair between 20-30% and  
 206 poor when greater than 30% [30].

207 The EF [31] compares the deviance of the errors (described by the numerator) with that of the  
 208 observations (described by the denominator). Its maximum value is 1 and indicates complete  
 209 agreement between predictions and observations. The EF decreases with decreasing predictive  
 210 power of the model until reaching negative values, meaning that the model describes the data less  
 211 well than the arithmetical mean of the observations.

212 **3. Results**

213 The phases whose relationship between DR and mean temperature (T) is better approximated by a  
 214 linear function were:

- 215 1) sowing to three leaves unfolded (S-3L, BBCH 0-13);
- 216 2) three leaves unfolded to second node detectable (3L-2N, BBCH 13-32);
- 217 3) second node detectable to the beginning of heading (2N-H, BBCH 32-51);
- 218 4) beginning of heading to physiological maturity (H-M, BBCH51-89).

219 Linear relationships between developmental rates and mean air temperature for single sub-phases  
 220 are shown in Figure 2. Coefficients and related statistics for the simple linear DR functions are  
 221 given in Table 1.

222

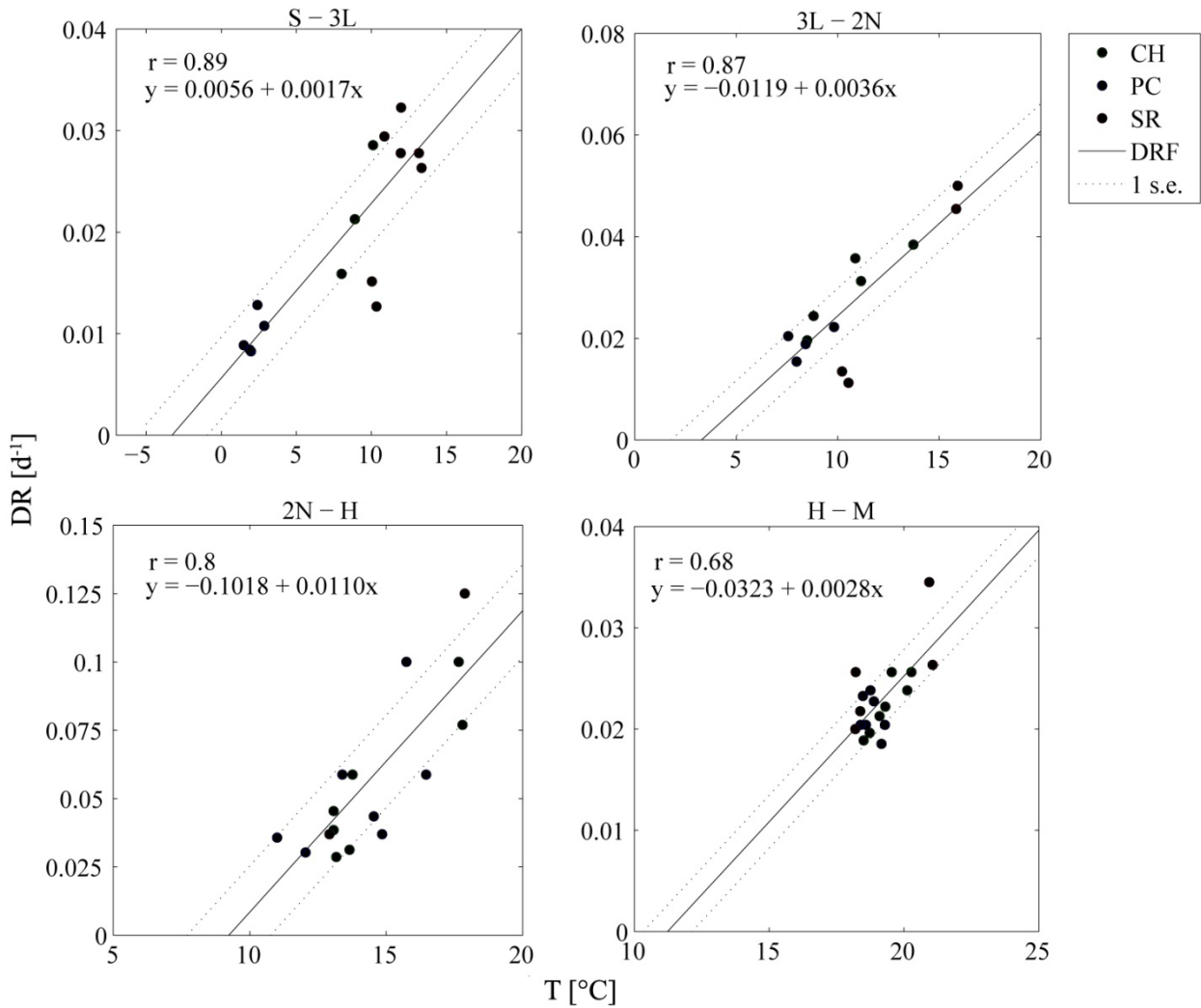
223 **Table 1.** Statistics of the simple linear regression for the selected phases. Phases as in Fig.1.

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$DR = a + bT$ (eq. 1)				
phase	$T_0$ [°C]	$a$ [d <sup>-1</sup> ]	$b$ [°C <sup>-1</sup> d <sup>-1</sup> ]	$\epsilon$ [d <sup>-1</sup> ]
S-3L	$-3.3 \pm 2.3$	0.0055	0.0017	0.0040
3L-2N	$3.3 \pm 1.5$	-0.0119	0.0036	0.0054
2N-H	$9.2 \pm 1.5$	-0.1018	0.0110	0.0169
H-M	$11.2 \pm 0.9$	-0.0323	0.0029	0.0026



231

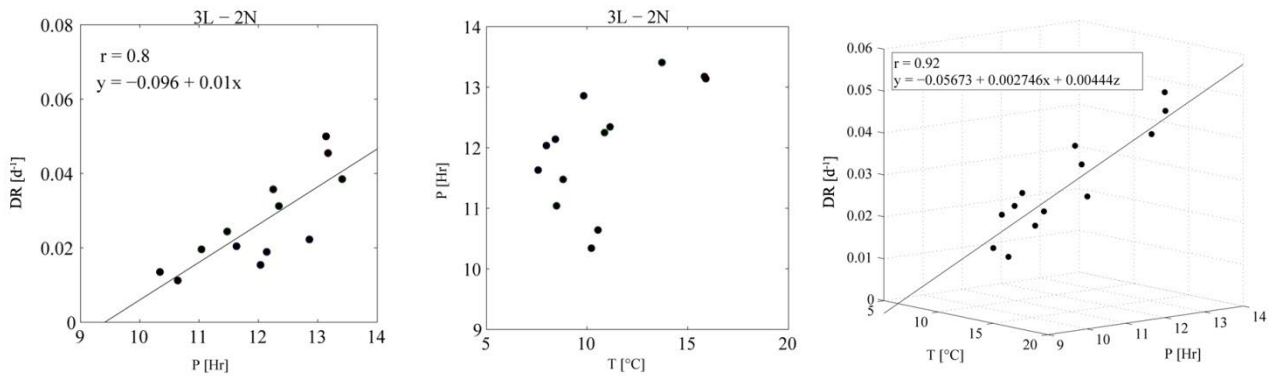
232 **Figure 2.** Relationships between wheat developmental rates and mean air temperature (from the calibration dataset) for  
 233 the selected wheat phases. Black lines: DR function, dotted lines: 1 standard error ( $\epsilon$ ), used to track back to the  
 234 uncertainty in the base temperature. S-3L: from sowing to three leaves unfolded; 3L-2N: from three leaves unfolded to  
 235 second node detectable; 2N-H from second node detectable to the beginning of heading; H-M: from the beginning of  
 236 heading to physiological maturity.

237 In the first three phases the correlations between development rate and temperature were very high  
 238 ( $r=0.80-0.89$ ), whilst in H-M the correlation was lower ( $r = 0.68$ ) and the range of mean  
 239 temperatures experienced was narrower (about 4°C) when compared to the other phases (ca. 15°C  
 240 in S-3L; 10°C in 3L-2N; 7°C in 2N-H). Temperature alone explained 64-79% of developmental  
 241 rates (values from  $r^2$ ) in the first three phases, 46% in H-M.

242

243 Base temperatures increased throughout the wheat crop life cycle, ranging from -3.3°C in S-3L to  
 244 11.2°C in H-M (Tab.1 and Fig S1). Uncertainties in the base temperature, quantified by  $\varepsilon$  (see  
 245 dotted line in Fig. 1) were relatively large in S-3L and decreased in the subsequent phases (Tab.1).  
 246 The slopes of DRs regularly increased throughout the vegetative phases and slow down after  
 247 heading (Fig. S1). Residuals (Fig. S2) revealed homogeneous variance and no bias.

248 The phase 3L-2N was the only showing a significant ( $p < 0.01$ ) correlation with daylength (Fig. 3,  
 249 left panel). In this phase, no correlation resulted between temperature and daylength, suggesting no  
 250 collinearity between explanatory variables (Fig 3, middle panel). The multiple linear regression  
 251 (Fig. 3, right panel) between developmental rate, temperature and daylength increased the  
 252 explanatory power of the regression from 0.75 ( $r^2$ ) to 0.82 (adjusted  $r^2$ ). Related coefficients and  
 253 statistics for the improved DR are summarized in Table 2. Values for  $T_{0m}$  and  $P_{0m}$  (Fig S3) were 5.6  
 254 °C and 9.5 Hr, respectively.



255  
 256 **Figure 3.** Left: relationship between wheat developmental rates and mean daylength (P [Hr]); middle: mean  
 257 temperature vs. mean daylength scatter plot (showing no collinearity); right: multiple linear regression defining  
 258 developmental rates in 3L-2N as a function of temperature and daylength.

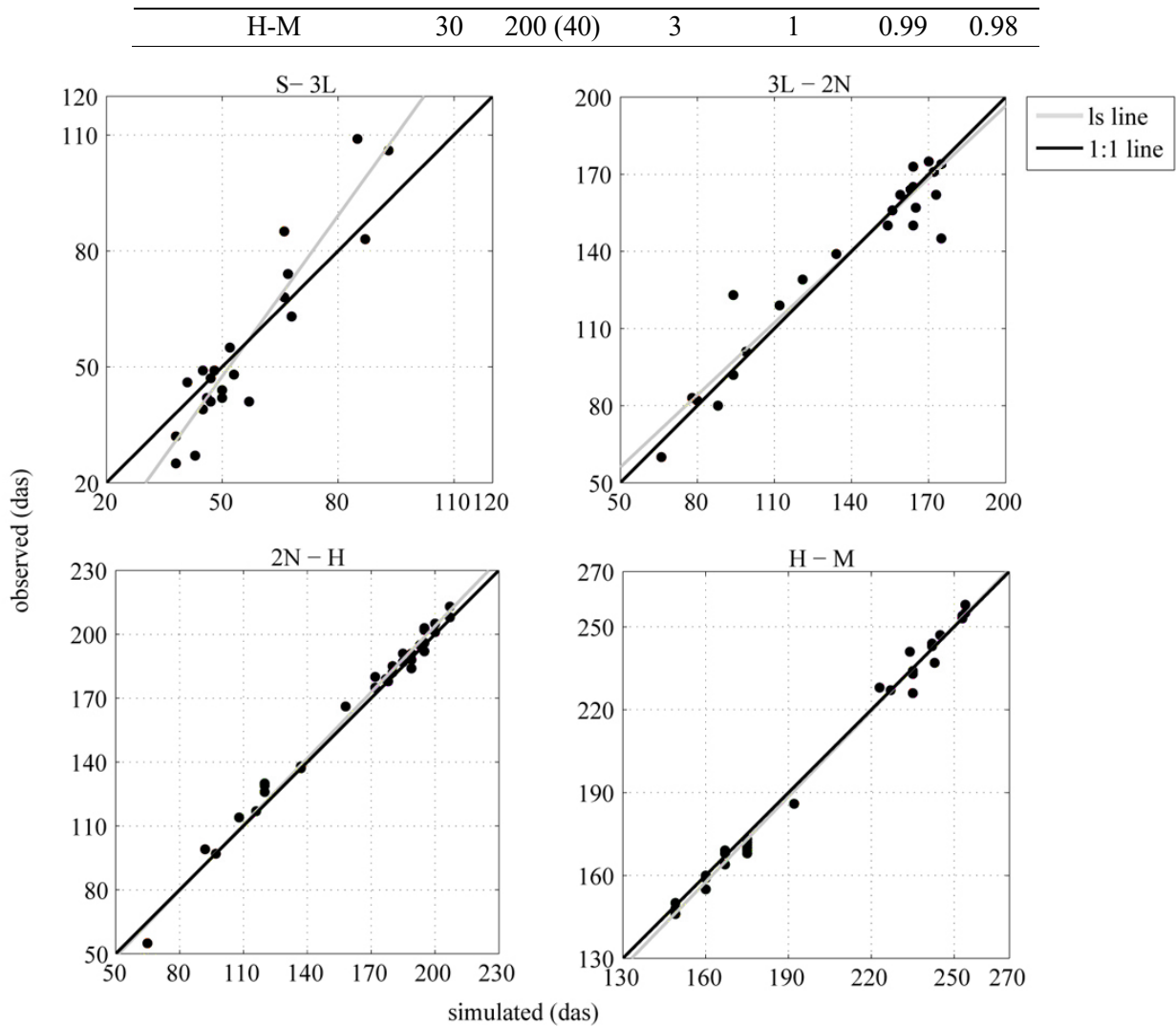
259 **Table 2.** Statistics of the multiple linear regression for 3L-2N.

$DR = a + bT + cP$ (eq. 4)						
phase	$T_{0m}$	$P_{0m}$	$a$	$b$	$c$	adj. $r^2$
3L-2N	5.6	9.5	-0.0567	0.0027	0.0044	0.84

260  
 261 The performance of the generalised phenological model, which uses simple linear functions of  
 262 temperatures in the three phases (S-3L; 2N-H; H-M) and multiple linear function of temperature  
 263 and photoperiod in 3L-2N, is shown in Figure 4, while the corresponding statistics for each phase  
 264 are summarised in Table 3. Overall, simulations were able to catch the general pattern of wheat  
 265 development (EF=0.80-0.99) and mean errors remained below eight days.

266 **Table 3.** Statistical evaluation of the phenological model over the validation dataset for single phases.  $n$ : sample size;  
 267  $\bar{O}$ (std): mean observed phase length (1 standard deviation); MAE: Mean Absolute Error; NMAE: normalized MAE;  $r^2$   
 268 determination coefficient; correlation between observations and predictions were always significant ( $p < 0.01$ ).

Phenological phases	$N$	$\bar{O}$ (std) [d]	MAE [d]	NMAE [%]	EF	$r^2$
S-3L	22	55(23)	7.8	14	0.80	0.75
3L-2N	23	135(35)	7.0	5	0.91	0.83
2N-H	32	162(44)	4.5	2	0.98	0.96



269  
 270 **Figure 3.** Simulated vs. observed durum wheat phenological events (3L, 2N, H and M) after sowing (S), from the  
 271 independent validation dataset. Black line: 1:1 line, grey line: least square line.

272 Largest deviations from the observations were found in 3L, where MAE and NMAE are high (MAE  
 273 = 7.8 days; NMAE = 14%). The simulation of the subsequent events improved gradually. In 2N, the  
 274 model efficiency was very good (EF = 0.91), albeit few predictions were far from observations,  
 275 keeping MAE relatively high (MAE=7). In H and M predictions and observations are strongly  
 276 correlated ( $r^2 \geq 0.98$ ). Indeed, the efficiency of the model to predict H and M results high (EF  $\geq$   
 277 0.98), NMAE excellent (NMAE  $\leq 2\%$ ) and MAE 4.5 and 3 days, respectively. Predictions of M are  
 278 the most accurate.

279 In Table S2 we also provide the results that would be obtained if predictions were made by the  
 280 model not improved by daylength. Results obtained without considering the photoperiod have  
 281 higher inaccuracy, especially in the predictions of H where the mean errors would be doubled  
 282 (around 8 days).

#### 283 4. Discussion and Conclusion

284 A generalised phenological model for durum wheat valid for the Italian peninsula was obtained by  
 285 using a large phenological database and searching for the phases where the residual variability in  
 286 the developmental rates were minimized among linear temperature responses. The resulting DR

287 functions gave satisfactory results (EF = 0.89-0.99) over different Italian temperature regimes and  
288 wheat varieties.

289 The generalised model has a practical advantage of being usable under a wide range of  
290 environmental conditions where the reference to single wheat variety, climate and the agronomic  
291 regime could be reductive. To date, most contemporary crop models are developed for monoculture  
292 systems, where the specific crop variety, environmental condition and management practices are  
293 well defined in the model. The present model has several examples of potential applications, such  
294 as regional simulations as, for instance, long-term impact analysis due to climate change (e.g. how  
295 plant phenology is shifting due to global climate change, [32]) and land suitability analysis [33],  
296 including the identification of the optimal sowing window to minimise the risk of spring frost and  
297 late-season drought. Interesting applications of the generalised model could also be proposed for  
298 agro-ecological purposes where, for instance, landraces, intra-specific crop mixtures and crop  
299 diversification are recommended to improve the resilience of the system, promote pest regulation  
300 and enhance nutrient recycling [18,34,35]. Although the model is yet to be tested on ancient  
301 varieties, we recommend it as a suitable tool for modeling the phenology of landraces and  
302 underutilized variety (i.e. situations where observational data are few) due to its high level of  
303 generalisation. Indeed, the consequence of transition from landraces to modern varieties in the  
304 phenology of Italian durum wheat is still poorly understood. In some cases, the transition appears to  
305 be a steady advance in anthesis date [36], yet in others no significant changes are observed [37].

306 Our results were achieved following a method distinct from that of scholars who typically develop  
307 phenological model, since the wheat phases were not established *a priori* and the model calibration  
308 was carried out only after the strongest linear responses, involving different wheat varieties, had  
309 been identified.

310 Following our approach, temperature alone can explain approximately 64-79% of the variability in  
311 the developmental rates from sowing to the beginning of heading, observed from different cultivars.  
312 Indeed, the early phenological models, which were based on air temperature, could explain most of  
313 the observed developmental-time variability [21, 22, 38]. Later, photoperiod and vernalization were  
314 proven to further explain the observed variability in wheat development [9,10,11].

315 Accordingly, our results show a significant correlation between developmental rates and daylength  
316 in 3L-2N, and the ability to explain the observed variability in that phase increases from 75% to  
317 85% when introducing the photoperiod. Photoperiod increases the accuracy of the model, mostly on  
318 the predictions of the beginning of heading. A similar improvement was also reported in McMaster  
319 and Smika [10].

320 Overall, we argue that there will always be a variability in wheat development rates not explained  
321 by temperature and photoperiod (e.g. due to the environmental heterogeneity, proximity of the  
322 meteorological stations, uncertainty in the measurements, genotypic differences, etc.), but, in our  
323 case, such variability was minimized by two concomitant strategies: *i*) using data from different  
324 experimental sites and sowing periods, which provided a wide range of explored temperatures; *ii*)  
325 identifying phenological phases with variability in the developmental rates better explained by a  
326 linear dependence on temperature. The obtained result is a set of simple linear relationships  
327 describing the widely-recognised general rule that plants grow faster when the temperature is  
328 warmer, enhanced by an increasing photoperiod, but with a unique parameterisation for durum  
329 wheat over the Italian peninsula.

330 The largest errors were found in the predictions of 3L (7.8 days) and 2N (7.0 days), which was  
331 consistent with the larger uncertainties in the base temperatures in S-3L and 3L-2N (Tab. 1). Our  
332 results are in agreement with previous studies reporting that wheat phenological events facing the  
333 winter and falling into the period of tillering (up to the beginning of stem elongation) generally  
334 show large variability and are also the hardest to predict [39,40]. Moreover, the resulting errors are  
335 also comparable with those found elsewhere [39,40, 41,42,43,44] with values ranging from 3 to 11  
336 days, depending on the phenological phase.

337 Errors on H(4.5) and M(3.0) are also in line with the observed variability from 193 durum wheat  
338 varieties, including landraces, representative of the Mediterranean basin, as reported by Soriano et  
339 al. [45].

340 Our results also show that base temperature progressively increased throughout the crop life cycle  
341 (Tab. 1, Fig.2 and Fig. S1), with values are in line with the base temperatures reported in Porter and  
342 Gawith's review of the literature [15]. The progressive increase of base temperatures has already  
343 been documented elsewhere [21, 22] and used to explain non-linear temperature responses observed  
344 over long wheat phases [47]. In particular, Slafer and Rawson [46] report that long phases, as  
345 seedling to anthesis, can show curvilinear temperature response, but also a clearly linear  
346 relationship during shorter phases.

347 Our work does feature some simplification and limitations that should be described.

348 First, phenophases, generally, reflect some scientific or managerial interest, such as periods when  
349 the plant is particularly vulnerable or demanding for nutrient, where a farmer can, for example,  
350 intervene or purchase insurance. Similarly, some phases are adequate for the analysis of climate  
351 change impacts, pests, and diseases. From an agronomical point of view, our approach could lead to  
352 significant results for unattractive phases.

353 Second, in our work vernalization is not explicitly modeled. This can lead to some errors in the  
354 parameterisation. For instance, if some plants requiring vernalization are not satisfied, the  
355 variability in the observed developmental rates will increase (as data could be more scattered). In  
356 our case, the strong correlation between developmental rates and daylength in 3L-2N suggests that  
357 most of the plants have likely satisfied their vernalization requirement, or, at least, might not have  
358 required any vernalization, being sensitive to photoperiod. The wide range of mean temperature  
359 needed for vernalization (roughly from -1° to 15 °C, optimally from 4° to 6° C, see Porter and  
360 Gawith. [15]), as well as the possibility of seeds not requiring field vernalization, helped our  
361 approach; however, an implicit limitation remains.

362 Third, the model could not reflect the impact of prolonged extreme temperatures since linear rate  
363 functions may underestimate the development times under extremely high temperatures. However,  
364 in our data and due to the adopted approach, which search for the best linear temperature responses,  
365 there are no observations (i.e. points in the scatter plots of Fig. 2) that suggest a likely drop in the  
366 rates in the selected phases under the Italian growing season. Indeed, observations subjected to few  
367 days with extremely high temperatures would unlikely result in a drop in the developmental rates  
368 since data are average values over several days. Here, we argue that when extreme high  
369 temperatures arise for only a few days, the model's result would likely be within the expected error.  
370 Otherwise development times could be underestimated.

371

372 In conclusion, a likely increasing demand for genetic diversity in monoculture will call for models  
373 that are able to generalise phenological development at the species level, and provide the expected  
374 range of variability. To date, such models are still poorly developed. Our work could be a step  
375 forward toward a new modelling approach that to support agro-ecology applications.

### 376 **Acknowledgements**

377 We deeply thank Prof. Giovanni Toderi (UNIBO) for providing us with a database of historical  
378 phenological data.

### 379 **Declaration of interests**

380 The authors have no competing interests to declare

### 381 **Author Contributions**

382 A.D.P. and M.S. conceived and planned the study. M.V. and F.V. collected the data. ADP  
383 performed the analysis. All the authors contributed to analyzed and discussed the results and wrote  
384 the paper.

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## SUPPLEMENTARY INFORMATION

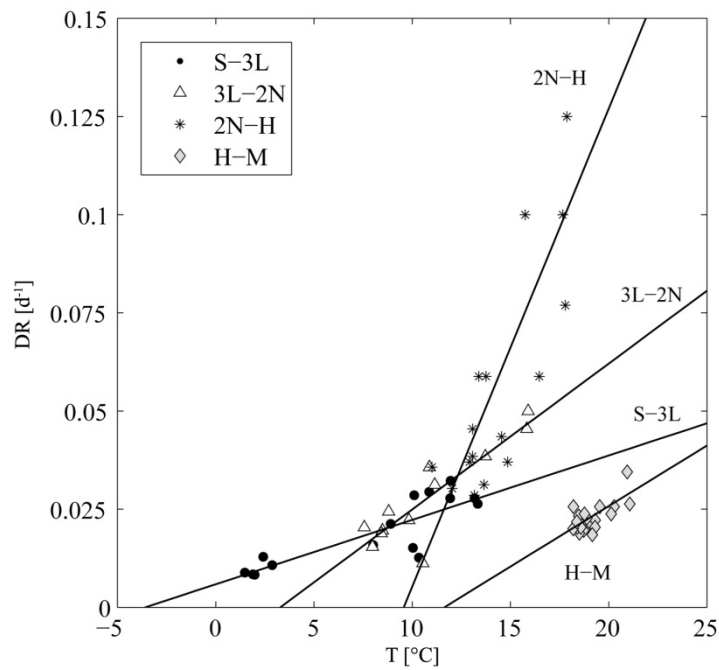
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**Table S1.** As Table 1 in the main text but showing results obtained by a simple TS model (not considering the effect of photoperiod).

506

Phenological phases	<i>n</i>	$\bar{O}$ (std) [d]	MAE [d]	NMAE [%]	EF	$R^2$	<i>p</i>
S-3L	22	55(23)	7.8	14	0.80	0.75	<0.01
3L-2N	23	135(35)	7.0	5	0.91	0.83	<0.01
2N-H	32	162(44)	4.5	2	0.98	0.96	<0.01
H-M	30	200 (40)	3	1	0.99	0.98	<0.01

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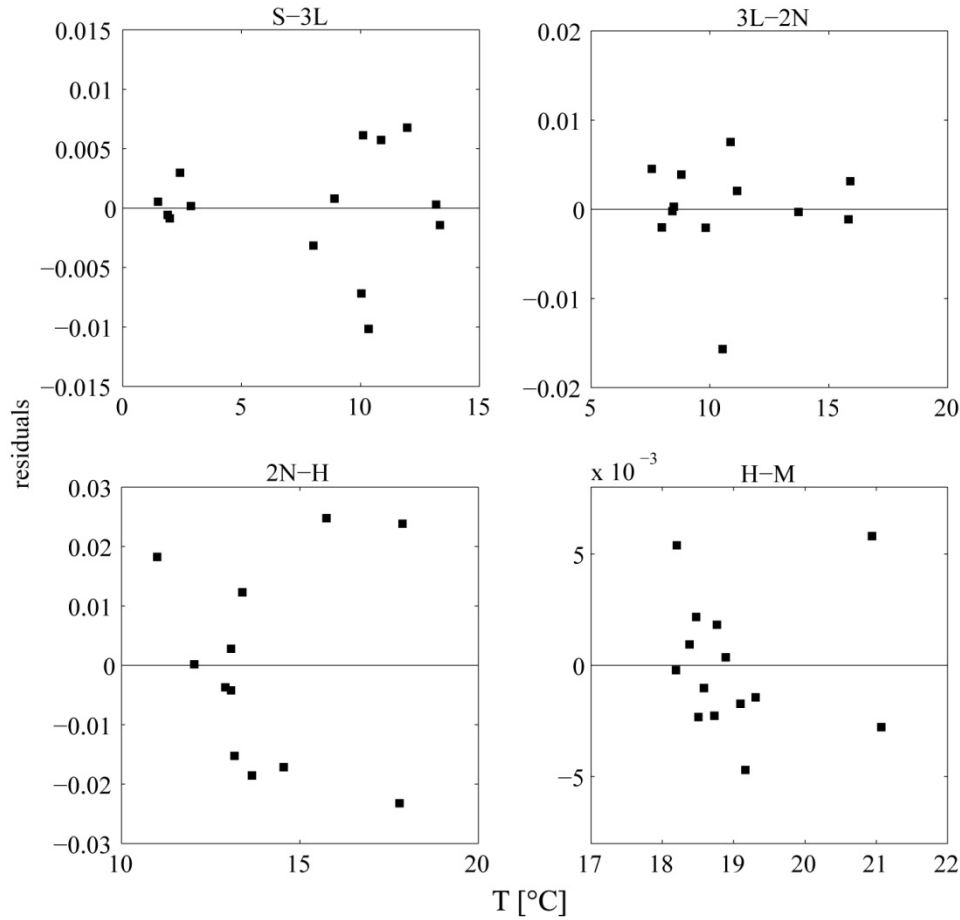
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**Figure S1.** Comparison between DRs. Black lines: DRs; data points: data from the calibration dataset (symbols in legend). S-3L: from sowing to three leaves unfolded; 3L-2N: from three leaves unfolded to second node detectable; 2N-H: from second node detectable to beginning of heading; H-M: from beginning of heading to physiological maturity.

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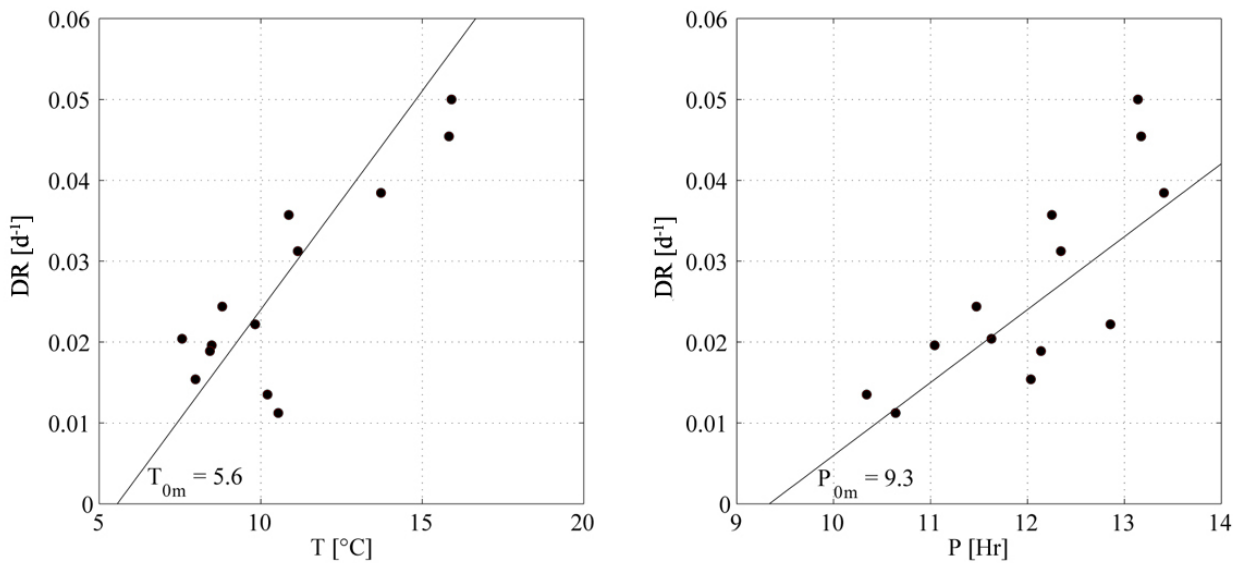


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**Figure S2.** Residuals from simple linear regression considering only mean temperature. Dispersion of data reveals no biased relationships and almost homogenous variance.



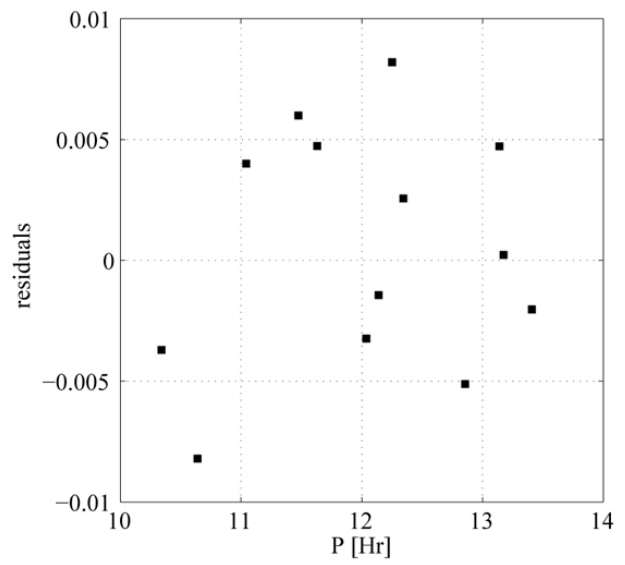
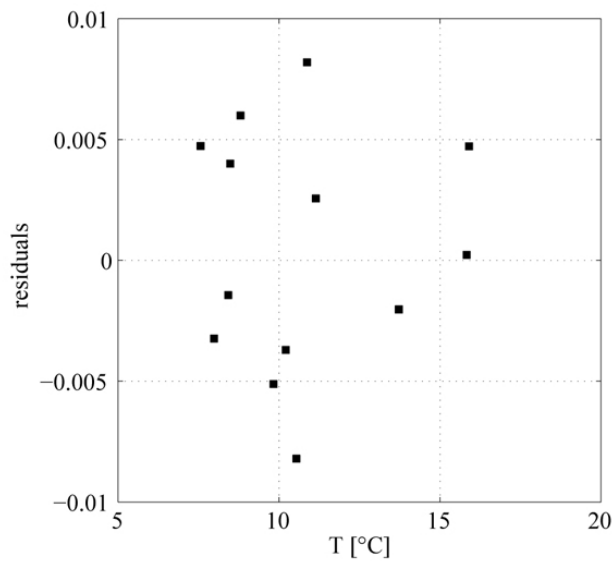
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**Figure S3.** Multiple linear regression (as shown in the right panel of Fig. 3) projected on two-dimensional scatter plot. The intersection of the linear function with the abscissa return the threshold values for  $T_{0m}$  and  $P_{0m}$ .



520

521 **Figure S4.** Residuals from multiple linear regression in 3L-2N. Dispersion of data reveals no biased  
 522 relationships and almost homogenous variance.

523

524