WHEATZARD (WHEAT ZEROING IN ON ADAPTIVE RESPONSE TO DROUGHT): A STUDY TO EVALUATE WATER STRESS IMPACT ON WHEAT PHENOLOGY SIMULATIONS

WHEATZARD (WHEAT ZEROING IN ON ADAPTIVE RESPONSE TO DROUGHT): UNO STUDIO PER LA VALUTAZIONE DELL'IMPATTO DELLO STRESS IDRICO SULLE SIMULAZIONI FENOLOGICHE DEL FRUMENTO

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Abstract
Plants' phenological development depends on air temperature as major driving cue. The relationship between air temperature and plants phenology has been formalized via the Growing Degree Days (GDDs) concept, defined as the thermal time accumulated during a time step, generally one day (24 hours). Traditional GDD models do not take into account other constraining factors than temperature as vernalization, photoperiod and water stress (WS). Despite several experimental evidences have demonstrated that phenology can be hastened or slowed down by WS, its representation in plant phenology model is still debated. One potential approach is to modulate the accumulation of GDDs using a "water stress factor," analogous to existing adjustments for vernalization and photoperiod. This is particularly relevant given that the occurrence of WS, considering its timing, duration, frequency, and severity throughout the crop life cycle, varies markedly across environments and agricultural seasons, thereby complicating the identification of consistent phenological patterns. The objectives of this study were to evaluate the phenological responses of wheat to WS using a 20-year dataset (2003–2023) of field observations collected in a long-term experiment located in Bologna (Emilia-Romagna). A hourly time step phenological model was calibrated and validated to account for temperature, vernalization, and photoperiod effects. Then, a simplified WS model has been used to study the dynamic correlation of WS during the growing season in order to understand its influence on the timing of key developmental stages. The results showed that the correlation between WS and wheat phenology strongly varied during the crop cycle, both in terms of direction and intensity. Overall, results showed the tendency of the crop to alternate an initial phases of drought avoidance, in which phenology was slowed down, with a phase of drought escape, in which the opposite behavior, i.e., accelerating phenology, was implemented. Incorporating a WS factor could enhance the model's responsiveness to water-limited conditions and potentially reduce prediction errors.

Parole chiave
Calcolo dei GDD, fenologia, stress idrico, modellistica colturale
Keywords
GDDs calculation, phenology, drought stress, crop modeling

Introduction

Plants' phenological development, referring to the periodically recurring events throughout their life cycle (Lieth 1974) primarily depends on air temperature, which is recognized as its major driving force (Schwartz 2003). The connection between air temperature and plants phenology has been translated into the Growing Degree Days (GDDs) concept, defined as the thermal time accumulated during a period of time, generally a day (24 hours) (Mcmaster and Wilhelm 1997). Various modeling approaches have been developed to simulate plants phenology through GDDs accumulation, most of these sharing the assumption that a plant starts cumulating thermal time once temperatures rise above a minimum threshold required to transition between phenological stages, and ceases accumulation when temperature exceeds an upper threshold (Chuine and Régnière 2017). However, thermal models do not take into consideration other constraining factors to plants development. For example, when modeling winter cereals phenology, vernalization and photoperiod have to be considered. Specifically, wheat has been proven to be sensitive to vernalization and photoperiod from emergence to heading (Slafer 1994). Thus, several modelling approaches modulate wheat development by vernalization and photoperiod effects, reducing thermal-time (GDDs) accumulation using empirical factors (McMaster et al. 2008; Herndl et al. 2008). Moreover, other environmental factors affect wheat phenological development, and should be considered to improve simulation models. This is a crucial aspect nowadays, considering that an accurate representation of phenology is essential to explore the effects of climate change or the impact of alternative management practices. For example, being phenology a plastic and flexible trait, several experimental evidences have demonstrated that it can be hastened or slowed down by water stress (WS). Although it is uniformly recognized that terminal drought reduces grain filling duration, as a consequence of accelerated leaf senescence, reduced photosynthesis, downregulation of enzyme activities, and sink limitation (Farooq et al. 2014), at the same time, several experiments over the years have obtained results that are only partially superimposable in the relationship between phenology and WS. Simane et al. (1993) found that early WS (at tillering) increases the time necessary for wheat to reach both anthesis and maturity. They also found that mid (flowering) and late (grain filling) WS did not affect time to flowering, but significantly shortened grain filling duration. Ihsan et al. (2016), imposing WS immediately after crop establishment (2 weeks after sowing), observed that WS accelerated wheat phenological development already from tillering, pushing it to early maturity. In particular, days to complete 50% heading and crop physiological maturity were greatly reduced compared to other phenological stages, suggesting that booting and grain filling can be significantly accelerated by early drought. Qaseem et al. (2019) found that water stress imposed from heading reduces the number of days to anthesis and to maturity. These apparently contradicting results are ascribable to differences in WS intensity, duration, and timing in different experimental conditions. In fact WS occurrence, in terms of time of appearance, duration, frequency, and severity, along the wheat life cycle varies significantly among different environments and years, making it difficult to identify reliable phenological patterns, which is further complicated by the presence of confounding factors, e.g., other concomitant abiotic stresses in an operational context. Consequently, despite some evidence in the literature proved that wheat phenology simulations improve when adding responses to WS (McMaster et al. 2019), it is still not unequivocally clear how to take it into account in wheat phenological simulation models, i.e. altering GDDs accumulation using a “water stress factor”, similarly to what is operationally done for vernalization and photoperiod. The objectives of this study were to evaluate the phenological responses of wheat to WS using a 20-year dataset (2003–2023) of field observations collected in Cadriano, Bologna (IT). Firstly, a phenological model was calibrated and validated to account for temperature, vernalization, and photoperiod effects. Then, the potential of incorporating WS into the existing model to improve the simulation accuracy of wheat phenology was assessed, investigating how WS influenced the timing of key developmental stages.

Materials and Methods

Phenological data

The observation dataset used in this study has been collected over 2003 – 2023, and has been derived from the phenological bulletins weekly released by the Department of Agricultural and Food Sciences (DISTAL), the University of Bologna. The bulletin publishes data derived from phenological surveys carried out on the cultivar Mieti, in accordance with the Phenagri protocol (Pasquini 2006), at the agro-phenological station of Cadriano (44◦ 330 0300’ N, 11◦ 240 3600 E). Mieti is the wheat variety currently used for the bulletin, as it is representative of most varieties used in the area. Phenology was analyzed according to the BBCH scale (Biologische Bundesanstalt, Bundessortenamt, and CHemical industry), which encodes plants’ development stages using a double-digit code from sowing (00) to harvest (99), thus consisting of 10 principal stages (0– 9), with 10 secondary stages (0–9) for each principal one (Meier 1997). In each agronomic season, the chronological time expressed as days after sowing (DAS) to reach each BBCH phase was used for the calibration and validation of a phenological model and for analysing the relationship between the duration of phenological phases and WS.

Phenological model

A phenological model based on GDD accumulation was used to simulate BBCH stage progression in wheat. The model accounted for thermal time accumulation, vernalization, and photoperiod sensitivity, with daily inputs of temperature and photoperiod. Weather data (daily maximum and minimum temperatures and daily precipitation) were provided by DISTAL agrometeorological station. Calibration was performed using observed phenological data extracted from weekly phenology bulletins, setting model parameters as cycle length, vernalization hours and photoperiod effect, as well as stage-specific thresholds: BBCH 10, BBCH 20, BBCH 30, BBCH 45, BBCH 55, BBCH 65, BBCH 75, and BBCH 85. These parameters defined the thermal thresholds required to reach those specific BBCH stages. In particular, BBCH 10, 20, 30, 45 and 55 were expressed as percentages of the vegetative phase duration; BBCH 65 as the percentage of the total life cycle when the vegetative phases occur; BBCH 75 and 85 as a percentage completion of the ripening phase. Model calibration was performed using an optimization algorithm, the multi-start downhill simplex (Acutis 2006; Nelder 1965), which generates a simplex (a geometrical figure with N+1 vertexes, with N as the parameter number under calibration). Average Root Mean Square Error (RMSE), between simulated and observed phenological data was set as objective function evaluated after each simulation run. The automatic optimization ended when the difference of RMSE between consecutive simulations felt below a tolerance threshold; 3 simplexes of 333 iterations each were set. Phenological model was validated on the same set of field experiments, covering the 20-year period. Model performance was assessed by comparing DAS to reach simulated and observed BBCH stages, via RMSE.

Water stress calculation

The calculation of Relative Soil Water Content (RSWC) on day *i* for each experiment was carried out according to the formula reported by (Gardin et al. 2021), as follows:

$$RSWCi = VCi \times (0.5 + 0.5 \times AWi) + (1 - VCi) \times AWi$$

Where VCi and AWi are respectively the Vegetation Cover and the Available Water at day *i*. VC was determined by modeling a Light Interception (LI) curve, as a function of wheat phenological development (BBCH scale). LI bi-phasic logistic model curve was constructed by combining data from published green LAI dynamics curves, visual phenological archives, also through application of the Beer-Lambert law (fixed reference points were established for key

BBCH stages, based on phenological observations and literature synthesis) (Graf et al. 2023; Rivas et al. 2024; Goh et al. 2022; 2024). From potential LI curve thus obtained, a LI curve limited by WS was calculated, by multiplying potential LI by the RSWC on the previous day. LI curve limited by WS was directly used as VC. AW was determined by dividing the rolling sum (15 days) of precipitation by the sum of ET0. Water Stress (WS) at day *i* was computed as follow:

WSi = 1 - RSWCi

Water stress and phenology relationship assessment
Sliding windows of Pearson's correlation coefficients were calculated between WS experienced during each phenological phase and the corresponding phase duration across all years. This analysis aimed to assess the impact of WS on the duration of phenological phases and to derive a phase-specific sensitivity index quantifying the potential influence of WS on developmental timing. Specifically, wheat life cycle was divided into four periods, based on the BBCH scale: early (BBCH 00–20), tillering (BBCH 20–30), middle (BBCH 30–55), and late (BBCH 55–89). Starting from observed phenological data we calculated the Pearson correlation coefficient (r) between the weekly rolling mean of water stress (waterStressRollmean) and the duration of that period, at each 5% interval of period completion (expressed in chronological time). Finally, to represent the entire crop cycle on 0–100% scale, these four periods were merged by aligning their individual completion percentages according to the average DAS at which transitions between periods occurred, preserving the chronological structure of the phenological development.

Results and Discussion

Phenological model
Calibrated parameters are reported in table 1. Weekly observed and simulated phenology was compared computing RMSE between observed and simulated Days After Sowing (DAS) necessary to reach the various BBCH stages (Figure 1). The phenology model incorporating temperature, vernalization, and photoperiod cues yielded a mean RMSE of 13.2 ± 3.8 days across all experiments. It is important to contextualize this result within the scope and complexity of the modeling task, as this model simulates the entire phenological development from BBCH 00 (sowing) to BBCH 89 (full maturity). Consequently, RMSE reflects the cumulative deviation across multiple developmental stages, each with its own variability and sensitivity to environmental drivers, inherently increasing the difficulty of the simulation, as the model must accurately track the timing of numerous transitions rather than optimizing for single events. Moreover, observed phenological data used for model evaluation were collected on a weekly basis, introducing a temporal resolution of approximately ±3–4 days.

Tab.1 – Calibrazione dei parametri del modello fenologico.
Tab.1 – Calibrated model parameters.

Parameter	Value
Cycle length (GDD)	1469
Vernalization hours (n. of hours)	108
Photoperiod effect (%)	55
BBCH 10 (% of vegetative phase)	13
BBCH 20 (% of vegetative phase)	18
BBCH 30 (% of vegetative phase)	41
BBCH 45 (% of vegetative phase)	62
BBCH 55 (% of vegetative phase)	65
BBCH 65 (% of total life cycle)	75
BBCH 75 (% of reproductive phase)	24
BBCH 85 (% of reproductive phase)	47

In summary, despite the model showed a good level of accuracy, there's potential for improvement in capturing the full range of phenological plasticity given by environmental factors. Incorporating a water stress factor could enhance the model's responsiveness to water-limited conditions and potentially reduce prediction errors. As a first step toward this goal, the punctual 20-year dataset available in this study offered a unique opportunity to investigate and quantify the relationship between WS and the duration of phenological phases across the crop life cycle.

Water stress calculation
Daily WS for each year was estimated by integrating precipitation and ET_0 data with VC dynamics, the latter derived from LI curve, which in turn was inferred from the simulated BBCH stage. As examples, obtained results for three agronomic seasons, showing contrasting dynamics in terms of WS, and thus highlighting the experimental variability in the dataset, are reported in Figure 2. In 2003-2004, WS levels were mostly reduced along the life cycle, except for some transient and rapid bursts (as reflected by a close alignment between the potential and stressed LI curves) , at least until BBCH 70, after which stress increased in frequency. 2006-2007 agronomic season, in addition to terminal drought, showed pronounced and prolonged WS from the beginning till the end of tillering. Potential and limited LI curves significantly diverged, suggesting a strong physiological response. The 2019-2020 season presented an early-onset of intense WS, already from crop emergence (BBCH 10), continuously till booting stage (BBCH 40), resulting in a sharp drop in light interception. Then, WS progressively reduced to zero during ripening phase. These contrasting patterns across the three seasons demonstrated the informative variability of the 20-year dataset, essential for evaluating the impact of WS on phenology. The presence of both mild and severe stress scenarios across different crop stages provided a robust basis for quantifying WS–phenology relations and for defining a "water stress factor" to be incorporated as a dynamic driver of crop phenological development.

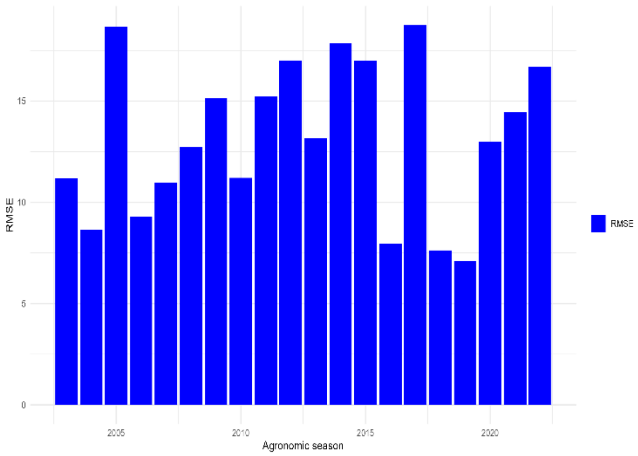

Fig.1 – RMSE calcolato tra i dati osservati dal bollettino fenologico settimanale e quelli simulati dal modello, espresso come Days After Sowing (DAS) necessari al raggiungimento delle varie fasi BBCH.
Fig.1 - RMSE between Days After Sowing (DAS, necessary to reach the various BBCH stages) observed in the weekly phenological bulletin and simulated by the phenological model.

Water stress and phenology relationship

Wheat life cycle was divided into early (BBCH 00–20), tillering (BBCH 20–30), middle (BBCH 30–55), and late (BBCH 55–89) period. Combining agronomic seasons in the 20-year dataset, for each period, Pearson correlation coefficient (r) between the weekly rolling mean of water stress (waterStressRollmean) and the duration of the period itself was calculated, at each 5% interval of period completion (expressed in chronological time). Finally, to represent the entire crop cycle on a unified 0–100% scale, these four periods were merged by aligning their individual completion percentages according to the average DAS at which transitions between periods occurred, preserving the chronological structure of the phenological development. Results are presented in Figure 3. The results obtained by combining 20 years of data in the same experimental site showed that the correlation between WS and phenology varied along the crop cycle, both in terms of direction and intensity. Specifically, a strong positive correlation between WS and phenophase duration was observed in the initial phases, immediately after emergence (probably attributable to a difficulty for the crop to produce new leaves and vegetation cover in conditions of water scarcity), followed by a reversal of the trend as the beginning of tillering approached. A new shift of r values towards a positive sign was observed, at first, immediately after heading followed, subsequently, by the progressive intensification of negative r values, as the maturation phase approached (a typical condition of terminal drought in the Mediterranean basin, characterized by a well-known tendency of pushing wheat towards early maturity). Overall, results showed the tendency of the crop to alternate an initial phases of drought avoidance, in which phenology was slowed down, with a phase of drought escape, in which the opposite behavior of accelerating phenology was implemented.

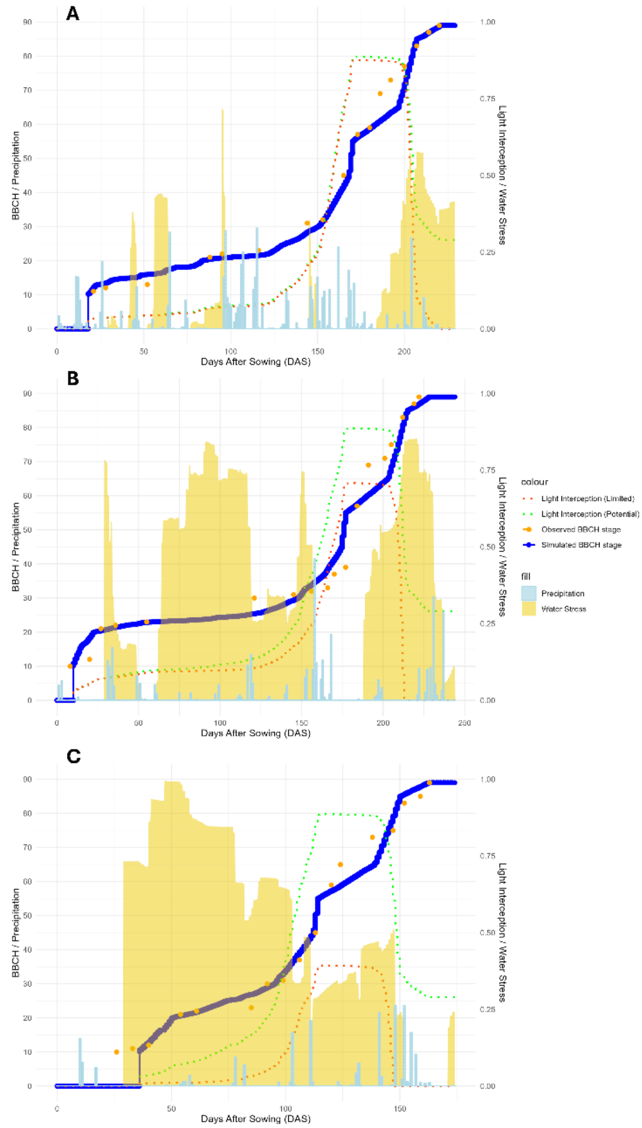

Fig.2 – Water stress calcolato per ogni giorno del ciclo colturale. In parallelo, sono riportati: la progressione fenologica simulata (linea blu), i dati fenologici osservati (punti arancioni), la curva di intercettazione della luce potenziale (linea tratteggiata verde) e limitata da water stress (linea tratteggiata arancione), e le piogge durante il ciclo (istogrammi azzurri). Tre stagioni agronomiche sono riportate come esempio: 2003-2004 (A), 2006-2007 (B), 2019-2020 (C).
Fig.2 - Water stress calculated for each day along the crop cycle. In parallel, the following are shown: simulated phenological progression (blue line), observed phenological data (orange dots), potential light interception curve (green dashed line), light interception curve limited by water stress (orange dashed line), and daily precipitation during the cycle (light blue bars). Three growing seasons are presented as examples: 2003–2004 (A), 2006–2007 (B), and 2019–2020 (C).

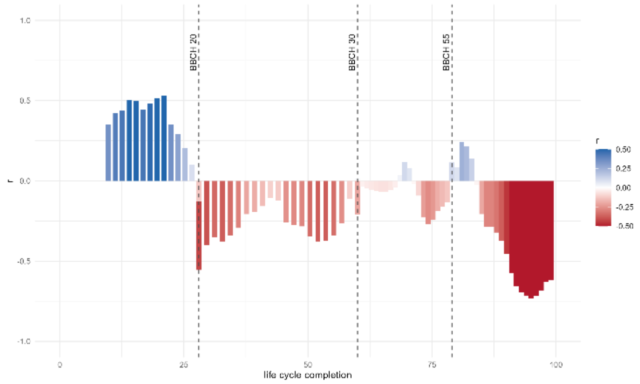

Fig.3 – media mobile settimanale della correlazione (r di Pearson) tra water stress e durata della fase fenologica considerata
Fig.3 - weekly moving average of the correlation (Pearson's r) between water stress and duration of the considered phenological phase

Conclusions

Incorporating a "water stress factor" could enhance the phenological model's responsiveness to water-limited conditions and potentially reduce prediction errors. As a first step toward this goal, the punctual 20-year dataset available in this study offered a unique opportunity to investigate and quantify the relationship between WS and the duration of phenological phases across wheat life cycle. This analysis will be essential to inform the development of a more physiologically realistic model capable of capturing the effects of WS on phenological dynamics.

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