Accounting for soil moisture improves prediction of flowering time in chickpea and wheat

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Matching crop phenology to environment is essential to improve yield and reduce risk of losses due to extreme temperatures, hence the importance of accurate prediction of flowering time. Empirical evidence suggests that soil water can influence flowering time in chickpea and wheat, but simulation models rarely account for this effect. Adjusting daily thermal time accumulation with fractional available soil water in the 0–60 cm soil layer improved the prediction of flowering time for both chickpea and wheat in comparison to the model simulating flowering time with only temperature and photoperiod. The number of post-flowering frost events accounted for 24% of the variation in observed chickpea yield using a temperature-photoperiod model, and 66% of the variation in yield with a model accounting for top-soil water content. Integrating the effect of soil water content in crop simulation models could improve prediction of flowering time and abiotic stress risk assessment.

The world faces the growing challenge of feeding over 9.5 billion people by 2050 under the looming threat of climate change. To address this challenge while reducing the carbon footprint and conserving water, our reliance on protein from plants will need to increase significantly. Chickpea is the third most important protein rich grain legume which is directly consumed as human food in the poorer countries where the projected population increases are most likely to occur. The crop is also important for sustainability of farming systems due to its nitrogen fixing ability. Chickpea yields are constrained by the crop’s high sensitivity to a number of abiotic stresses including frost, drought and heat stress.

Matching crop phenology to environment is critical for stress adaptation and crop yield, hence the importance of accurate prediction of flowering time. Based on experimental studies, crop simulation models including the Agriculture Production Systems Simulator (APSIM) and Decision Support System for Agrotechnology Transfer (DSSAT) model chickpea phenology as a function of temperature and photoperiod. However, prediction of flowering time based on these two parameters is relatively poor, suggesting other drivers of crop development may have been overlooked.

A few studies have shown that soil water can influence flowering time in chickpea and wheat. Kwang-Wook and Singh reported a positive relationship between chickpea flowering time and crop evapotranspiration. Singh reported that the thermal time requirement for emergence to flowering and flowering to maturity of chickpea decreased as normalized evapotranspiration deficit increased. Johansen, et al. also reported differences in flowering time between irrigated and rainfed chickpeas. A similar effect of soil water deficit on flowering time has been reported for wheat. In wheat, photoperiod and vernalisation genes only accounted for about 53% of the variation in flowering time, indicating that a significant proportion of the observed variation could be due to other factor(s), including soil water.

Limited attempts have been made to incorporate the soil water effect in models for flowering time, with emphasis on the drier end of the soil water range. The APSIM model has an option to delay flowering of maize, sorghum and peanut in dry soil. Here we propose that the soil water effect on flowering time in chickpea and wheat can involve both (i) a hastening effect of water deficit, and (ii) a delaying effect of wet soil. Both interpretations have been advanced in the literature, but the former dominates. The possibility of soil water delaying flowering in wheat has been alluded to by McDonald, et al., but this was not investigated.

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This study describes the detection of the dynamic effect of high soil water on flowering time and its use in the APSIM model to improve flowering time prediction. Our focus is chickpea, with a secondary analysis in wheat.

**Results and Discussion**

**Detection of soil water effect on flowering time of chickpea.** Prediction of flowering time using temperature and photoperiod for 11 sowings at three sites in northern Australia resulted in a discrepancy of up to 34 days between the observed and predicted flowering times (Fig. 1a). The magnitude of this discrepancy was about 1.5 times larger than the range of genetic variation in flowering time in diverse field environments across Australia; hence the importance of understanding the source of this discrepancy. Previous studies in chickpea have suggested that soil water deficit can advance flowering time.

Since the three soils in our study varied in plant available water holding capacity, we suspected that soil water could have caused this discrepancy. The maximum discrepancy occurred at Jondaryan and Warwick in South East Queensland, Australia where chickpea crops were grown with considerable sowing to pre-flowering rainfall (Table 1) on Vertisols with higher water holding capacity.

To understand how soil water status can influence flowering time of chickpea we modelled its effect. This was challenging because soil water availability is highly dynamic, as it is influenced by crop (i.e. size and functionality of canopy and root system), management (e.g. row spacing), soil properties and weather. Our data set representing a range of water holding capacities (109 to 257 mm) associated with site-specific soils (Ferrosol, several Vertisols), row spacing and rainfall (Table 1), captured many of these effects. In the absence of soil water measurements,
each of the 11 simulations commenced with a low starting available water on 1st Nov of the previous year, which was about six months before sowing. This starting water was determined using the Australian Landscape Water Balance model accessed at www.bom.gov.au/water/landscape. We addressed the challenge by developing a simple equation (Eq. 1 described in methods) that captured the dynamic relationship between fractional available soil water (FASW), which is the ratio of available water to the total available water, and daily thermal time (TT). The equation was developed through manual adjustments in daily thermal time when simulated FASW was >0.65 to fit the observed flowering data. An FASW of >0.65 represents the readily available water in the surface 0–60 cm layer where most roots are present27. This equation improved the Lin’s Concordance Correlation Coefficient (Lin’s CCC), which measures a model’s predictive performance28 as defined in Eq. 6 in Methods, to the almost perfect (>0.99) category (Fig. 1b). Applying this relationship below or above 60 cm increased the normalised root mean square error (NRMSE).

The relationship between soil water and thermal time espoused through Eq. 1 modifies thermal time accumulation to influence flowering time in different environments depending upon their soil and climatic attributes. In the 11 sowings, we observed a much larger delay in flowering time in self-cracking clay Vertisols of Warwick and Jondaryan in which the plant available water holding capacity is higher as compared to Ferrosols of Kingaroy. Comparison of soil water changes in 2015 at Kingaroy and Warwick suggested, that over time, FASW declined more gradually at Warwick as compared to Kingaroy (Fig. 2). The modification of thermal time at Warwick was therefore greater and occurred over a longer period resulting in slower accumulation of thermal time target of about 1017 °Cd for flowering compared to 1048 °Cd for Kingaroy. The difference in achieving these targets was consistent with about a month delay in flowering observed at Warwick.

To explore the effect of pre- and in-season rainfall on the same soil, we re-analysed the data of Beech and Leach29 for chickpea cultivar Tyson, sown in 1979 and 1980 at Dalby, Queensland in which soil water measurements were also made (Fig. 3). The 1979 season was wetter than 1980 resulting in higher soil water in the surface layers30. In 1979, total water use was 191 mm by 28th Aug and 279 mm by 26th Sep. In 1980, total water use was 93 mm by 1st Sep and 161 mm by 30th Sep. The soil water use simulated in 1979 was 179 mm on 28th Aug and 26th Sep, respectively, and in 1980, 106 mm and 149 mm on 1 Sep and 30th Sep, respectively. The crops flowered 94 days after sowing in 1979 and 83 days after sowing in 1980. Days to flowering simulated without the input of soil water was 83 in 1979 and 84 in 1980. With the soil water input, days to flowering time simulated was 94 to 96 in 1979 and 81 to 84 in 1980 for a range of row spacing and planting densities used.

A larger modification of daily thermal time due to higher extractable soil water and over a slightly longer period was evident in 1979 (Fig. 3), which could have contributed to the delayed achievement of thermal time target for flowering as compared to 1980. The cumulative (unadjusted) thermal time targets computed by adding soil water effect for 1979 and 1980 were 1244 and 1035 °Cd, respectively, which closely matched the observed 1214 and 1032 °Cd reported in the study29. The increase in thermal time target for flowering with higher soil water was consistent with similar differences observed in irrigated and rainfed chickpea on a Vertisol soil in India31.

**Agronomic implications.** The improvement in accuracy with our modelling approach accounting for the soil water effect has agronomic implications as illustrated in the assessment of the risk of post-flowering frost (minimum temperature ≤0 °C) events32. The number of post-flowering frost events accounted for 24% of the variation in yield in the 11 sowings using the original model, whereas the model accounting for soil water increased it to 66% (Fig. 4a, b). The yield ratio in Fig. 4 represents the ‘gap’ between the potential and observed yields...
occurring due to frost. Decreasing the potential yield by 5% for each post-flowering frost event and relating the reduced yield to the observed yield, increased the Lin's CCC from 0.39 with the original model to 0.85 with the model accounting for the soil water effect (Fig. 4c vs. 4d). The soil water based model to predict flowering time should therefore improve strategies to manage frost risk that could be expanded to other stresses.

Prediction of flowering time of chickpea for more diverse ranges of environments. We further compared the two modelling approaches, with and without soil water, using pooled data including the original 11 sowings and 26 additional sowings with Pulse Breeding Australia (PBA) HatTrick from yield evaluation trials on soils of different plant available water holding capacities over a range of latitudes and longitudes within Queensland, Australia (Fig. 5). In these sowings, the improvement in Lin’s CCC was from poor (0.89) to substantial agreement categories (0.97).

We modelled chickpea flowering using a photoperiod range from 10 to 12 hours compared to the original range of 10 to 17 hours in APSIM. Within chickpea growing regions and sowing windows adopted in Australia, photoperiod changes are within 2.5 hours before the September equinox by which time most chickpea have flowered. Hence, the rationale of using a higher range of photoperiod for Australian cultivars in the model may need re-examination. It might be that a larger photoperiod range was acting as a surrogate for the soil water effect. However, this would fail to capture locational and seasonal variation in soil water with variable influence on flowering time as shown in Figs 2 and 3. It is possible that photoperiod and temperature interactions, that are commonly reported in the field in chickpea, are actually three-way interactions between soil water, temperature and photoperiod as photoperiod by temperature interactions have not been observed in controlled environments. Temperature interacts with soil water by influencing evapotranspiration demand. With the most divergences of flowering time in the model based on photoperiod and temperature falling below the 1:1 line (Figs 1a and 5a), it appears that temperature and photoperiod set the minimum time that a chickpea crop could take to flower. In contrast, soil water modulates the time between minimum and actual time to flower (Figs 1b and 5b). Soil water, however, is very dynamic, hence the importance of initial conditions in the modelling of flowering time incorporating soil water. We achieved reasonable improvement of prediction when we initialised soil water based on root zone water modelled by the Australian Landscape Water Balance on 1st Nov, about six months before sowing. As an alternative, remote sensing can also be tested for soil water initialisation.

Prediction of flowering time of wheat. Wheat is the dominant crop of southern Australian farming systems spread over southern New South Wales, Victoria and South Australia. The application of the soil water correction improved the prediction of flowering time in wheat (Fig. 6). In APSIM, wheat flowering time is predicted based on temperature, photoperiod and vernalisation, and parameters accounting for these effects seem to have been optimised in those environments. For example, model parameters of the popular cultivar Enterprise Grains Australia (EGA) Gregory, which is less photo-period sensitive, are such that the original APSIM predicts flowering reasonably well for New South Wales sites/sowings, but not so well for Queensland sites/sowings resulting in a poor (0.81) Lin’s CCC (Fig. 6a). The default value of photoperiod sensitivity factor for this cultivar in the model is set to 3.2 and vernalisation sensitivity to 2.7. Zheng, et al. reduced the photoperiod sensitivity factor of this cultivar to 2.6 and the vernalisation sensitivity to 0.9 using a gene-based parameterisation (Fig. 6b). This moderately improved the Lin’s CCC (0.94) although prediction of flowering time for the central Queensland location of Emerald required further improvement. The discrepancy of Emerald (central Queensland) sowings was reduced by increasing the vernalisation sensitivity from 0.90 to 1.98, but this change affected prediction of...
Figure 4. Relationship of (a) number of post-flowering frost events and the ratio of observed vs. simulated yield using original model, (b) improved model, (c) simulated frost impacted yield (5% loss/frost event) vs. observed yield using the original model and (d) with improved model. NRMSE is normalised root mean square error. The black line in (a,b) is the fitted regression and light grey line in c and d is $y = x$. CCC in (c,d) are Lin’s concordance correlation coefficient.

Figure 5. The predictive accuracy of flowering time for 37 chickpea sowings (a) based only on temperature and photoperiod and (b) based on the additional effect of soil water. NRMSE is normalised root mean square error. The grey line is $y = x$. CCC = Lin’s concordance correlation coefficient.
flowering time in New South Wales sowings (Fig. 6c). The Lin's CCC increased to 0.96 when the soil water effect through Eq. 1 was incorporated (Fig. 6d). We can speculate that in the original model, the photoperiod and vernalisation parameters for this cultivar may have been fitted to overcome the soil water effect on flowering time for the dominant growing environments. Site-specificity of APSIM parameters for predicting wheat flowering which was suspected to occur due to the lack of proper model mechanisms has been highlighted earlier38. For a more robust prediction of flowering time, accounting for the soil water effect using the model we have developed may be necessary in wheat as well.

The use of the high photoperiod sensitivity parameter in the model for the otherwise relatively photoperiod insensitive wheat cultivar Gregory, as indicated above, may have unknowingly accounted for the soil water effect on flowering time at higher latitudes. In reality, however, soil water may be helping Gregory and other insensitive wheat cultivars to overcome some of the effects of earliness associated with photoperiod insensitivity. Photoperiod insensitivity in commercial wheat cultivars was introduced through the shuttle breeding of wheat at CIMMYT in Mexico in the 1960s39. Although Normal Borlaug considered photoperiod insensitivity an unplanned effect of shuttle breeding of wheat40, it is now recognised to have contributed to the green revolution in wheat as it enhanced adaptation of the crop to a wide range of latitudes39. The increase in pre-anthesis period of high yielding photoperiod insensitive wheat cultivars, achieved by the dynamic effect of soil water with irrigation, might have also assisted in avoiding frosts, as in the case of chickpea described above, and in producing more biomass while not having any of the adverse effects of photoperiod related sensitivity in yield components41.
Concluding remarks. Our modelling study is consistent with, but does not prove, that soil water modulates flowering time. The effect of soil water on development is biologically interesting, and relevant for modelling and agronomy.

Biologically, the causes and consequences of this effect need further research. From an adaptive viewpoint, photoperiod is a conserved environmental cue: temperature follows seasonal patterns with some intra- and inter-seasonal variation, whereas soil water is characterised by larger temporal variability. We can thus hypothesise that photoperiod and temperature provide broad geographic adaptation, whereas soil water would fine-tune flowering time to specific soil-season combinations. At the plant level, part of the effect could be related to temperature, as a dry soil is hotter; this is particularly important for wheat as its growing apex is underground during key developmental stages. Plants sense soil dryness and root-shoot signals are involved in modulation of shoot traits. Soil temperature has been suggested to affect flowering time in wheat. However the possibility that soil temperature could affect flowering time in wheat was ruled out earlier through experiments involving manipulation of soil temperature.

From a modelling perspective, we have shown that a model accounting for soil water, photoperiod and temperature is superior to conventional models in predicting flowering time. We have also shown the improvement in modelling risk associated with frost. Trade-offs between frost and heat damage are particularly important, and could be modelled more reliably with our approach. Agronomically, practices can be envisaged to exploit genotype x environment x management interactions influencing soil water, and hence flowering time in a context of risk.

Methods

Soil water effect on flowering time in chickpea. We collected flowering and yield data from 11 chickpea sowings from 2014 to 2017 at Kingaroy (26.55°S and 151.85°E), Jondaryan (27.37 to 27.50°S and 151.59–151.76°E) and (Warwick 28.21°S and 152.10°E) in Queensland, Australia. These sowings were part of two trials conducted to compare response of chickpea cultivars PBA HatTrick (released in 2009) and PBA Boundary (released in 2011) to frosts and planting time. For sowing, a summer fallow was practiced for growing winter crops as in-season rainfall is often limiting. At the beginning of summer season (on 1st Nov), it was assumed to contain very limited amount of soil water left by the previous crop. Since this initial amount was not measured, we used values obtained from the Australian Landscape Water Balance model (www.bom.gov.au/water/landscape). The soil water increased with subsequent summer rains. Sowings were at a 5 cm depth with adequate seed to achieve a plant population of 30 plants/m². Other agronomic details are given in Table 1. Observations on flowering were made when 50% of the plants had at least one open flower. Yield at maturity was estimated from hand-harvested samples from a 2 m² area.

Prediction of flowering times using APSIM. The APSIM model (version 7.10) consists of many modules of different models that are called upon as needed, to predict flowering time. The model enables simulation of systems that cover a range of plant, soil, climate and management interactions. The plant module of APSIM provides uptake values for soil water to the soil module. The model uses a thermal time approach to predict flowering of chickpea using cultivar specific parameters that are included in the plant models. In this study we used three chickpea cultivars including PBA Boundary, HatTrick, and Tyson (released in 1978) and their parameters including thermal time requirements for different phases of growth are given in Table 2. In the original model, the thermal time requirement for flowering of PBA Boundary and PBA HatTrick decreased from 446 to 0 °C during the photoperiod sensitive phase, as photoperiod increases from 10.7 to 17 h. Since chickpea does not experience more than 12 hours photoperiod from sowing to flowering in the winter season over a range of latitudes, we postulated that extra hours might have been built into the model to account for the soil water effect. Since we directly incorporated soil water information, we reduced the upper bound of photoperiod from 17 to 12 hours as given in Table 2. The same set of cultivar parameters was applied to all sowings. To incorporate the effect of soil water on flowering time we used the following equation in the manager module of the model:

\[ TT_{in} = TT \times (1.65 - FASW) \quad \text{when} \quad FASW \geq 0.65 \quad \text{and} \quad \text{the chickpea stage} \geq 3 \]  

Here \( TT_{in} \) is modified daily thermal time, \( TT \) is daily thermal time, and \( FASW \) is the fraction of available soil water in top 60 cm layers relative to lower limit at 1.5 MPa. These top layers constituted the effective rooting zone for chickpea where most of the roots are located. \( TT \) in the model was computed using a set of cardinal temperatures with base = 0 °C, optimum = 30 °C and ceiling = 40 °C. \( TT \) equalled mean ambient temperature up to 30 °C. The ‘1.65’ in Eq. 1 was a constant identified through manual optimisation which limited reduction in \( TT \) only when \( FASW \) was >0.65. The available soil water in this range is described as the readily available water for chickpea and other crops.

\( FASW = \Sigma(sw_{dep}(i) - ll15_{dep}(i))/\Sigma(dul_{dep}(i) - ll15_{dep}(i)) \)  

(2)
where \(sw_{\text{dep}}\) is soil water, \(ll15_{\text{dep}}\) is the soil water corresponding to a soil water potential of 1.5 MPa, and \(dul_{\text{dep}}\) is the soil water at field capacity (0.03 MPa) in each layer (i) in the top 60 cm soil surface layers. Equation 1 was operationalised only when FASW was \(>0.65\) and the emergence (growth stage 3) had occurred. The reduction in TT was maximum when FASW values were \(\geq 1\), i.e., when soil water in the surface 60 cm layers was near the field capacity.

The extractable soil water was defined as the water held between field capacity (DUL) and at 1.5 MPa soil water potential (ll15) in the soil. Soil parameters of all sowing locations except for Jondaryan in 2015 were obtained from the APSoil database (www.apsim.info). For the Jondaryan 2015 sowing, a generic Vertisol (No. 523) of 137 mm water available water holding capacity was selected from the same database based on water holding capacity described for an agricultural area around a nearby mining site. Daily data from nearby weather stations were downloaded from the apsrunet.apsim.info website. Weather at the experimental sites was also monitored in the 11 sowings, which was patched on to the weather data downloaded from the apsrunet.apsim.info website. The user interface of APSIM was configured to link the above soil and daily weather data and other agronomic details including cultivar, sowing date, depth of sowing, row spacing and plant population used. The change in accumulated thermal time was accomplished on a daily basis through the manager module of the model. Flowering time was also simulated using unmodified model parameters.

**Assessment of the effect of post flowering frosts on chickpea yield.** In the above-mentioned 11 chickpea sowings, the crop experienced a varying number of frost events (\(\leq 0^\circ\text{C}\)) before and after flowering in all three locations. The number of post-flowering frosts computed by the model was contingent upon the accuracy of prediction of flowering time. We assessed the impact of frost on yield using two approaches. In the first approach, we compared the relationship between the number of frost events and the ratio of potential realisable yield and the observed yield, which represented the yield gap. In the second approach, we compared the observed yield with the simulated yield loss due to post-flowering frosts. It has been estimated that each post-flowering frost event causes about 5% loss in yield of chickpea. The following equations were, therefore, incorporated in the manager module to simulate 5% yield loss for each post-flowering frost event:

\[
Yield_L = Yield_W \times (\Sigma PFF \times 0.05)
\]

(3)

\[
Yield_{GM} = Yield_W - Yield_L
\]

(4)

\(Yield_L\) is the yield lost due to frost, \(Yield_W\) is yield with 12% seed moisture content (potential yield), and \(Yield_{GM}\) is the observed (gross margin) yield a grower would harvest. PFF is a post-flowering frost event when the minimum temperature was \(\geq 0^\circ\text{C}\).

**Validation of the soil water model to predict flowering time in chickpea in diverse range of sowings and seasons.** Flowering was also predicted in a larger set of 24 additional sowings from breeding yield trials and two farming systems trials (Peter Want, DAF, Kingaroy, Personal Communication) conducted

| Parameter | Range | Unit | Description |
|-----------|-------|------|-------------|
| x_pp_hi_incr | 1 | 24 h | Photoperiod |
| y_hi_incr | 0.014 | 0.014 1/d | Rate of HI increase |
| x_hi_max_pot_stress | 0 | 1 | Average stress at flowering |
| y_hi_max_pot | 0.5 | 0.5 | Maximum harvest index potential |
| cum_vernal_days | 0 | 100 d | |
| t_emerg_to_endjuv | 515* | 515* °Cd | TT from emergence to end of juvenile phase |
| est_days_emerg_to_init | 83 | d | Estimated days from emergence to floral initiation |
| x_pp_endjuv_to_init | 10,7* | 17* h | Photoperiod |
| y_tt_endjuv_to_init | 446* | 0 °Cd | TT from end juvenile to floral initiation |
| x_pp_init_to_flower | 1 | 24 h | Photoperiod |
| Y_tt_init_to_flower | 33 | 33 °Cd | TT from initiation to flowering |
| x_pp_flower_to_start_grain | 1 | 24 h | Photoperiod |
| y_tt_flower_to_start_grain | 450 | 450 °Cd | TT from flowering to start grain fill |
| x_pp_start_to_end_grain | 1 | 24 h | Photoperiod |
| y_tt_start_to_end_grain | 690 | 690 °Cd | TT from start grain fill to end grain fill |
| tt_end_grain_to_maturity | 60 | °Cd | TT from end grain fill to maturity |
| tt_maturity_to_ripe | 1 | °Cd | TT from maturity to harvest ripe |
| x_stem_wt | 0 | 10 g/plant | Stem weight |
| y_height | 0 | 800 mm | Plant height |

Table 2. Parameters of desi chickpea cultivars PBA HatTrick, and PBA Boundary and Tyson in the APSIM model. *Changed to 660 °Cd for PBA Boundary and PBA HatTrick, 690 °Cd for Tyson. b10.1 h for Tyson. cChanged to 12 h in the new model, d468.3 °Cd for Tyson.
from 2013 to 2017 in Queensland. These locations covered 23.4 to 28.5°S latitude and 148.1 to 152.1° longitude. The set up procedure of the model was similar to that for the 11 sowings of chickpea. The soil parameters for the simulations were obtained from the APSOIL database and weather data from the apsurnet.apsim.info website. The details of these sowings and soils are given in the supplementary information (Supplementary Table 1). Simulations of all sowings were initialised on 1st Nov using data obtained from the Australian Landscape Water Balance (Supplementary Table 1).

Simulations were similarly run to predict flowering times in rainfed trials conducted in 1979 and 1980 at Dalby, Queensland. Soil parameters for the site were obtained from the APSOIL database and weather data from the apsurnet.apsim.info website (Supplementary Table 1). Simulations were initialised on 1st Nov of the previous year with a low soil water of 20% as landscape water balance data were not available for those two seasons. Other agronomic information included in the model was as described in the papers. Weather data were obtained from the apsurnet.apsim.info website.

**Soil water effect on flowering time in wheat.** The applicability of Eq. 1 to predict flowering of wheat was tested for cultivar Gregory grown at Goondiwindi, Emerald, Kingaroy, and Wellcamp in Queensland, and Wagga Wagga and Temora in New South Wales spread over 23.5 to 35.0°S latitude and 147.3 to 151.9° longitude. FASW was computed using the APSIM model as described for chickpea in Eq. 1 to predict flowering time. The soil parameters for the simulations were obtained from the APSOIL database (Supplementary Table 2). Soil water was initialised to a low level on 1st Nov of the previous year using the Australian Soil Water balance model (www.bom.gov.au/water/landscape). The model set up was similar to that for chickpea. All observed flowering data were either obtained from the Grains Research and Development Corporation website www.grdc.com.au and for Kingaroy from a colleague (Peter Want, DAF, Kingaroy, Personal Communication). The APSIM-Wheat is a process-oriented modular structure with externalised model parameters. To predict flowering time, the daily thermal time in the model was reduced by multiplying it with the vernalisation and photoperiod sensitivity factors for a given cultivar (www.apsim.info). Cultivar Gregory released in 2004 for cultivation in Queensland and New South Wales was considered to be relatively photoperiod insensitive, but it has high a photoperiod factor of 3.2 (for 0 to 5 scale) in the model. We hypothesized that if Gregory cultivar is indeed photoperiod insensitive, the high photoperiod sensitivity for this cultivar in the APSIM model could be to account for the effect of soil water on flowering. through actual field experiments estimated its photoperiod sensitivity factor as 2.6. They also reduced its vernalisation sensitivity from 2.7 to 0.9 while increasing its thermal time to floral initiation requirement from 555 to 715 °C days. We compared prediction of flowering of wheat in 40 sowings/site combinations using the original APSIM model, the APSIM model proposed by Zheng et al., and the soil water based model as proposed in this study.

The details of these sowings are given in the supplementary information (Supplementary Table 2). While applying the soil water based model using Eq. 1, the vernalisation sensitivity of the original APSIM model was reduced from 2.7 to 1.98, and the photoperiod sensitivity to 2.6 as used for Gregory in Zheng, et al. while the thermal time to initiation was kept as 555 °C days. These changes were derived from manual optimisation.

**Statistical analysis.** The relationship between observed/simulated yield and simulated yield after reducing it by 5% for each post-flowering frost event (as y variable), was quantified using linear regression with the R program. The normalised root mean square error (NRMSE) in Figs 1, 4, 5 and 6 was used to quantify a model's predictive performance. Lin's CCC achieves this by measuring how well the relationship between the observations and model predictions is represented by a straight line through the origin at an angle of 45 degrees. Lin's CCC is defined as

\[ \rho_c = \rho \times C_b \]  

where \( \rho \) is the Pearson product-moment correlation coefficient and \( C_b \) is a bias correction factor calculated as

\[ C_b = 2/(v + 1/v + u^2) \]  

\[ v = s_1/s_2 \]  

\[ u = (m_1 - m_2)/\sqrt{(s_1 \times s_2)} \]

where \( m_i \) and \( s_i \) (i = 1, 2) are the mean and standard deviation of the observations (i = 1) and predictions (i = 2). McBride suggests the following guidelines to infer a model's predictive performance.

- \( \rho_c < 0.90 \): poor
- \( \rho_c > 0.90 \) to 0.95: moderate
- \( \rho_c > 0.95 \) to 0.99: substantial
- \( \rho_c > 0.99 \) almost perfect.
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**Author Contributions**

Y.S.C. conceptualised the study. Y.S.C. and M.R. collected and assembled flowering data. Y.S.C. wrote the paper with contributions from M.R., S.C. and V.O.S.

**Additional Information**

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