Agricultural Systems 194 (2021) 103278

Contents lists available at ScienceDirect

Agricultural Systems

journal homepage: www.elsevier.com/locate/agsy

Review

Performance of a wheat yield prediction model and factors influencing the performance: A review and meta-analysis

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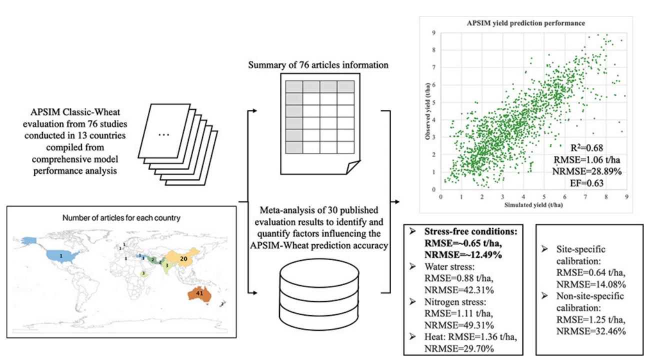
HIGHLIGHTS

- Crop model is a tool to simulate crop growth, seek solutions for mitigating negative environmental impacts on production.
- APSIM Classic has been used as an example to explore wheat yield prediction performance and the influential factors.
- Reviewed and established a meta-database from 76 published studies.
- Overall: the model predicts wheat yield with RMSE=1 t/ha. Fully calibrated and under stress-free condition: RMSE=0.64 t/ha.
- Calibration method, heat, frost, water, and nitrogen stresses were identified as factors causing the model to mis-simulate.

GRAPHICAL ABSTRACT



ARTICLE INFO

Editor: Dr Mark van Wijk

Keywords:
Cropping system
APSIM classic
Wheat
Yield prediction performance
meta-analysis
Literature review

ABSTRACT

CONTEXT: Process-based crop models provide ways to predict crop growth, evaluate environmental impacts on crops, test various crop management options, and guide crop breeding. They can be used to explore options for mitigating climate change impacts when combined with climate projections and explore mitigation of environmental impacts of production. The Agricultural Production Systems SIMulator (APSIM) is a widely adopted crop model that offers modules for simulation of various crops, soil processes, climate, and grazing within a modelling system that enables robust addition of new components.
OBJECTIVE: This study uses APSIM Classic-Wheat as an example to examine yield prediction accuracy of biophysically based crop yield modelling and to analyse the factors influencing the model performance.
METHODS: We analysed yield prediction results of APSIM Classic-Wheat from 76 published studies across thirteen countries on four continents. In addition, a meta-database of modelled and observed yields from 30 studies was established and used to identify factors that influence yield prediction uncertainty.
RESULTS AND CONCLUSIONS: Our analysis indicates that, with site-specific calibration, APSIM predicts yield with a root mean squared error (RMSE) smaller than 1 t/ha and a normalised RMSE (NRMSE) of about 28%,

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https://doi.org/10.1016/j.agsy.2021.103278
Received 1 June 2021; Received in revised form 3 September 2021; Accepted 15 September 2021
Available online 22 September 2021
0308-521X/

across a wide range of environmental conditions for independent evaluation periods. The results show increasing errors in yield with limited modelling information and adverse environmental conditions. Using soil hydraulic parameters derived from site-specific measurements and/or tuning cultivar parameters improves yield prediction accuracy: RMSE decreases from 1.25 t/ha to 0.64 t/ha and NRMSE from 32% to 14%. Lower model accuracy was found where APSIM overestimates yield under high water deficit condition and when it underestimates yield under nitrogen limitation. APSIM severely over-predicts yield when some abiotic stresses such as heatwaves and frost affect the crop growth.

SIGNIFICANCE: This paper uses APSIM-Wheat as an example to provide perspectives on crop model yield prediction performance under different conditions covering a wide spectrum of management practices, and environments. The findings deepen the understanding of model uncertainty associated with different calibration processes or under various stressed conditions. The results also indicate the need to improve the model's predictive skill by filling functional gaps in the wheat simulations and by assimilating external observations (e.g., biomass information estimated by remote sensing) to adjust the model simulation for stressed crops.

1. Introduction

Biophysical models, as agricultural simulation systems, are widely used to simulate crop growth, test management options, assess environmental trade-offs, and explore ways to cope with climate change impacts. The key strength of process-based biophysical models is their embodiment of our understanding of the dynamic interactions among crop, soil, water, atmosphere and solar radiation within the agricultural system (Horie et al., 1992). In essence, they simulate the biological and physical processes linking environmental effects to crop yield outcomes (Roberts et al., 2017). These models can assist in quantifying the impacts of changing climate on crop yield, designing efficient management practices, and informing crop breeding to secure food production. But deficiencies in the models and their implementations (e.g., calibration and weather inputs) can introduce random or systematic errors leading to uncertain yield predictions. While current efforts are underway to improve biophysical schemes, model inputs and implementation, understanding the current state of process-based model performance and sources of uncertainty can guide us to more effective strategies.

There exist several widely used process-based crop models that include Agricultural Production System SIMulator (APSIM) (Brown et al., 2018; Holzworth et al., 2014; Keating et al., 2003; McCown et al., 1996, 1995), Simulateur mulTIdisciplinaire pour les Cultures Standard (STICS) (Brisson et al., 2003, 2002, 1998), Environmental Policy Integrated Climate (EPIC) (Williams et al., 1989), The Soil & Water Assessment Tool (SWAT) (Neitsch et al., 2011), Decision Support System for Agrotechnology Transfer (DSSAT) (Jones et al., 2003)(), WOrld FOod STudies (WOFOST) (Van Diepen et al., 1989; van Ittersum et al., 2003), Soil Water Atmosphere Plant (SWAP) (Van Dam et al., 1997) and AquaCrop (Hsiao et al., 2009; Raes et al., 2009; Steduto et al., 2009). This work focuses on APSIM Classic as an example to explore a biophysical model's performance in predicting yield and the factors influencing the performance.

APSIM has been used for research and practical applications globally for over 25 years. It is also available as an online commercial agricultural decision-support tool, named Yield Prophet®, to serve Australian growers (Carberry et al., 2009; Hochman et al., 2009b). APSIM consists of interconnected modules describing the biophysical roles of soil water, soil nutrients, organic matter, crops, weather, and management. It can simulate various crop types and pastures. Simulated crops include wheat (Asseng et al., 2000, 1998a), maize (Archontoulis et al., 2014; Shamudzarira and Robertson, 2002), canola (Robertson and Lilley, 2016) and various legumes (Robertson et al., 2002). Previous studies have used it as a tool to reproduce the biophysical processes of the cropping system from paddock to regional level (Araya et al., 2020; Gaydon et al., 2006; Keating et al., 2002), including representing the role of soils (Connolly et al., 2002; Probert and Dimes, 2004; Thorburn et al., 2001), the influence of climate (Asseng et al., 2015; Bahri et al., 2019), and animal grazing (Bosi et al., 2020; Holzworth et al., 2014). It has also been used to guide genotype design of future cultivars (Rötter et al., 2015) and to understand genotype, environment and management interactions (Casadebaig et al., 2016; Hammer et al., 2010; Manschadi et al., 2006; Martre et al., 2015a; Zheng et al., 2015). Researchers have also combined APSIM with various climate projection models to investigate future food security challenges and explore solutions to mitigate environmental impacts on production (Akinseye et al., 2020; Anwar et al., 2020; Asseng et al., 2011, 2004; Liu et al., 2016a; Ludwig and Asseng, 2006). It has been coupled with economic models to develop profit maximisation strategies and to study the effectiveness of crop insurance (Hansen et al., 2009; Van Wijk et al., 2014). As a cropping system tool, the accuracy and uncertainty of APSIM simulations under different environmental and input resources conditions are important to model users, as they need to be aware of the uncertainty in model outputs under the circumstances of their interest.

Globally, wheat is the fourth most-produced crop and provides 20% of the calories consumed by people (FAO, 2020; Shiferaw et al., 2013). APSIM-Wheat yield prediction accuracy has been extensively evaluated for research applications and as a decision support tool for farmers. In addition to evaluations of APSIM-Wheat at field or regional scales with particular management practices or wheat cultivars, several APSIM developers and researchers have also collected assessment datasets covering a broader spectrum of management practices, environments, and cultivars to analyse model strengths, weaknesses and identify aspects for further development. An extensive set of the model validation data and descriptions are available on the APSIM website (https://www.apsim.info/). Holzworth et al. (2011) presented part of the wheat final yield validation results from those datasets, reporting a coefficient of determination (R^2) of 0.93 and root mean squared error (RMSE) of 0.46 t/ha. Brown et al. (2014) compared the predicted against observed yields for 164 simulations under a wide range of environments and treatments, resulting in an $R^2 = 0.92$. Gaydon et al. (2017) reviewed APSIM performance across various cropping systems in Asia and identified its strengths and weaknesses with 43 experimental datasets from 12 countries. They concluded that the model could be further improved in aspects related to harsh environments, conservation agriculture and low input systems. Brown et al. (2018) validated the model with experimental datasets from 8 countries covering a broad range of crop treatments. The results demonstrated that the model performed well overall with an $R^2 \geq 0.84$ and Nash-Sutcliffe Efficiency (NSE) ≥ 0.81.

While extensive work has been done to evaluate the model yield prediction accuracy, factors that affect the model's yield prediction uncertainty remain to be investigated comprehensively. In general, model prediction uncertainty originates from deficient/inaccurate model structure, input forcing data, parameter specification and observations used for model calibration/validation (Vrugt et al., 2008). In this paper, we review and quantify APSIM Classic (which hereafter is referred to as "APSIM")-Wheat yield prediction accuracy by compiling existing evaluation datasets from the literature and analysing the contribution of environmental and input resource factors to the model prediction uncertainty. The objective of the study is to review the performance of process-based crop model yield prediction and identify influential factors affecting prediction accuracy, with APSIM-Wheat used as an example. Firstly, an overview of the APSIM-Wheat yield prediction accuracy and uncertainty is provided by collating the model evaluation results from published studies. Next, a meta-analysis based on existing literature is performed to identify the factors influencing uncertain yield prediction, which include model specification and calibration, heat and frost stresses, water, and nitrogen availability. The uncertainties in yield prediction associated with the above-mentioned factors are discussed. Finally, suggestions are provided for improving the accuracy of crop models such as APSIM-Wheat prediction under circumstances of high prediction uncertainty.

2. Methods and materials

2.1. Overview of the APSIM classic and wheat module

APSIM is an agricultural modelling platform equipped with various biophysical and management modules to simulate cropping systems (Holzworth et al., 2014; Keating et al., 2003). The model is composed of multiple modules that simulate soil water, nutrients (carbon, nitrogen, and phosphorus), and crop growth processes under different environmental and management conditions. For example, the SoilWat (Jones and Kiniry, 1986; Littleboy et al., 1992) calculates soil water movement using a cascading water balance model, and it is used by most APSIM users (all studies reviewed in this work used SoilWat). Soil Water Infiltration and Movement (SWIM) is another option to simulate the soil-water-solute balance based on Richards' equation and the advection-dispersion equation, but is not adopted by most model users. The SoilN module simulates the transformations of carbon and nitrogen in the soil. SoilWat and SoilN interact with each other and together provide plant available soil water and nitrogen information to the Wheat module (Zheng et al., 2014)() for simulating crop growth. The Wheat module simulates phenological development, plant morphology, biomass and nitrogen concentration of different wheat components, grain number and grain size on a daily basis (Keating et al., 2001). Here we use APSIM-Wheat to collectively represent the wheat growth simulation model which consists of the required APSIM modules including SoilWat, SoilN, and Wheat. A detailed description of the Wheat module is provided by (Zheng et al., 2014). We only provide an overview of the stress factors considered in Wheat since they are used to better understand the factors influencing yield prediction performance.

2.1.1. Water stress

The Wheat module accounts for water stress impacts in simulating photosynthesis and leaf expansion. The influence on photosynthesis (f_{W_photo}) and leaf expansion (f_{W_expan}) is calculated as follows:

$$f_{W\_photo} = \frac{W_u}{W_d} \tag{1}$$

$$f_{W\_expan} = h_{w\_expan} \times \frac{W_u}{W_d} \tag{2}$$

where W_u and W_d are crop water uptake and water demand, respectively, and h_{w_expan} is a water stress factor piecewise linearly related to W_u/W_d. Smaller W_u/W_d results in a smaller h_{w_expan} value. So, Eq. (2) is effectively a quadratic function of W_u/W_d. Eqs. (1) and (2) indicate that both biomass accumulation and leaf expansion are scaled by the ratio of total daily water uptake to crop water demand, with leaf expansion more sensitive to the water stress.

2.1.2. Nitrogen stress

The Wheat module accounts for nitrogen stress on phenology (not applied), biomass accumulation, leaf appearance and expansion, and grain filling. The stress for these aspects is determined by the difference between organ nitrogen concentration and minimum and critical nitrogen concentration.

2.1.3. Heat stress

The Wheat module takes temperature as a factor affecting the crop into account in many ways (Zheng et al., 2014)(). The daily maximum temperature is considered as the temperature stress in calculating LAI senescence. The daily mean temperature $(T_{max} + T_{min})/2$ is considered as the stress factor affecting wheat growth in (1) crop phenology via the thermal time; (2) root depth growth; (3) biomass accumulation; (4) biomass demand of grain and the rate of grain filling.

2.1.4. Frost stress

The Wheat module incorporates the leaf area senescence effect using a frost stress function; however, the default parameterisation of the stress factor results in zero impact during the whole simulation, which means it is not in application.

2.2. Literature search and selection criteria

We performed a literature search for peer-reviewed journal articles focused on APSIM-Wheat performance evaluation using Scopus, ISI Web of Science and Google Scholar. The following keywords in English were employed to search the literature: APSIM, wheat, *Triticum aestivum*, yield prediction, validation, evaluation, verification, and performance. A total of 108 articles published between September 1997 and February 2020 are reviewed. Among these, only the 76 articles that included independent validation datasets (independent growing seasons/fields from calibration) of APSIM-Wheat grain yield prediction using in situ yield data at field scale are used for the meta-analysis of APSIM-Wheat yield uncertainty. The APSIM-Wheat validation datasets from these papers are across thirteen countries in four continents, including Australia (41 studies), New Zealand (2 studies), United States of America (1 study), Belgium (1 study), The Netherlands (1 study), Turkey (1 study), China (20 studies), India (3 studies), Pakistan (2 studies), Syria (1 study), Iran (2 studies), Ethiopia (3 studies), Tunisia (1 study) (some papers include locations from several countries, Fig. 1). It has to be noted that the studies and collated data sets used in our meta-analysis are not representative of the full range of climates and management practices worldwide due to the limited spatial application of the model. Nevertheless, Ninety-five percent of these studies cover arid and temperate Köppen-Geiger climate types while the other 5% are located in tropical and cold climates (Peel et al., 2007). The dataset we compiled covers mainly Australia, China, and North Africa, five papers also feature global data collections that include North American and European sites. The number of studies reflects the level of acceptance and popularity of APSIM in the respective countries. Although the wheat regions of Europe and North America are underrepresented in our data, wheat production in Australia and China accounts for a significant proportion (approx. 22% according to FAOSTAT Statistical Database, 2017) of global wheat production. In addition, situations such as extreme temperatures, different water and nitrogen availability, various soil types and hydraulic conditions are well covered by our dataset.

2.3. APSIM-Wheat calibration and evaluation metrics

The model evaluation datasets in reviewed papers contain calibration and validation processes. Here calibration refers to all processes to improve the model fit to data, while validation refers to testing models against independent data not used in calibration to ensure the rigour of the model evaluation. In model calibration, variables that are related to crop growth, such as physiological dates, leaf area index (LAI), biomass, yield or soil water content and evapotranspiration are typically considered as the benchmarks for calibration and validation. Based on different data sources used, three calibration (or parameter setting) methods were defined in this paper: (1) Manual/automatic tuning of parameters to make the model simulations better fit the observations; (2) Direct specification of parameters using field measurements of these parameters; (3) Parameter specification using available databases (e.g.,

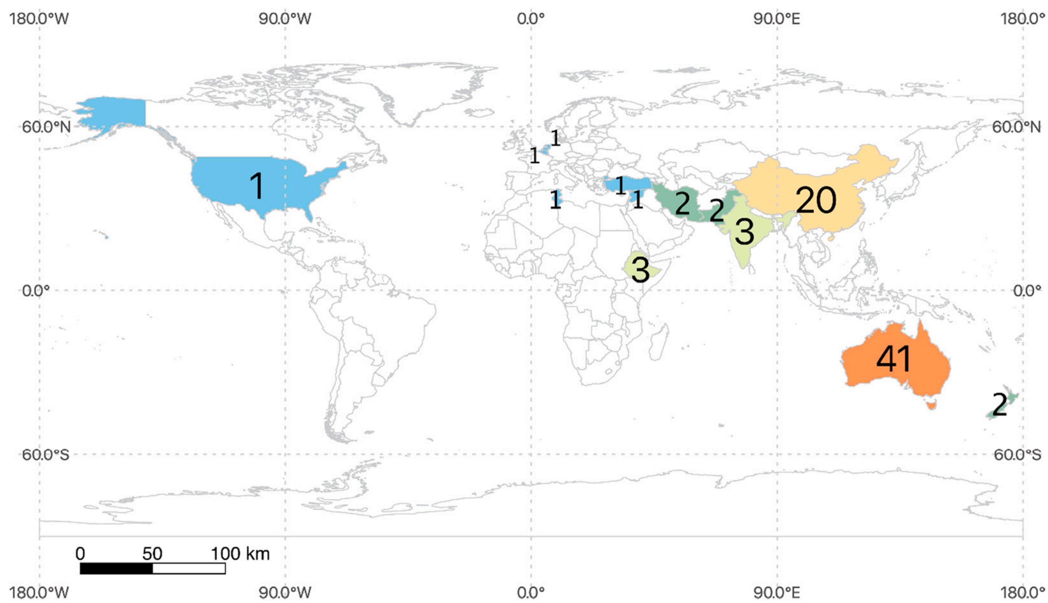

Fig. 1. Number of articles for each country (the dataset of United States of America is in the conterminous United States).

APSoil) or estimated data such as estimating lower limits from soil texture. The first two methods are collectively referred to as a fully site-specific calibration. If only one of them is adopted, it is partially site-specific calibration. The third method is classified as non-site-specific calibration (Table 1).

Many researchers specify the specific cultivar used in the simulation or manually adjust genetic parameters, especially those controlling wheat phenology and yield development by trial-and-error to improve the model predictions against field observations. The genetic parameters used to characterise the cultivar and their calibrated value ranges are summarised in Table 2. The details of reported calibrated values of these parameters are summarised in Supplementary Table S1. Some co-efficients listed in Supplementary Table S1 were derived from results for multiple soil types, sowing dates, sites, and growing seasons, which should help ensure the model robustness.

Soil parameters such as soil texture, soil hydraulic, and chemical parameters were usually specified in studies using laboratory test data (soil samples were taken from study fields), APSoil soil database (Dalgliesh et al., 2012, 2009), semblable objects or estimated data, such as estimating lower limits from soil texture (Sadras et al., 2003).

Several statistical criteria are commonly selected to evaluate model performance: the coefficient of determination (R^2), root mean square error (*RMSE*, also referred to as root mean square difference, *RMSD*), normalised *RMSE* (*NRMSE*), model efficiency (*EF*), and/or index of agreement (*d*) defined as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - O_i)^2} \quad (3)$$

$$NRMSE = RMSE \Big/ \overline{O} \quad (4)$$

$$EF = 1 - \frac{\sum_{i=1}^{N}(P_i - O_i)^2}{\sum_{i=1}^{N}\left(O_i - \overline{O}\right)^2} \quad (5)$$

Table 1
Calibration methods defined in this paper.

Manual tuning of parameters	Site-specific calibration
Parameter specification using ground observations.	
Parameter specification using APSoil or estimated data.	Non-site-specific calibration

Table 2
Definition of the genetic parameters.

Generic parameter name	Unit	Definition	Value range
tt_end_of_juverile	°C	The thermal time from end of juvenile to terminal spikelet stage	590–680 (North China Plain, China) 380 (North-eastern Iran)
tt_floral_initiation	°C	The thermal time target for floral initiation	500 (North-eastern Iran)
tt_start_grain_fill	°C	The thermal time target to start grain filling stage	545, 707 (Iran)
tt_startgf_to_mat	°C	The thermal time target from beginning of grain filling to maturity	420–650 (North China Plain, China, Iran) 750 (India)
potential_grain_filling_rate	g/(grain °Cd)	Potential grain filling rate	0.002–0.003 (North China Plain, China) 0.00129 (Iran)
grain_per_gram_stem	grain	Numbers of grain per gram stem	22–33 (North China Plain, China, Iran)
max_grain_size	g	Maximum grain size	0.038–0.05 (North China Plain, China)
vern_sens	N/A	Sensitivities to vernalisation	1.0–3.1 (North China Plain, China, India, Iran)
photop_sens	N/A	Sensitivities to photoperiod	1.8–3.5 (North China Plain, China) 3.8 (India) 3.5, 4.7 (Iran)
phyllochron	°Cd	Phyllochron interval	85 (North China Plain, China) 95 (India, Iran)

$$d = 1 - \frac{\sum_{i=1}^{N} (P_i - O_i)^2}{\sum_{i=1}^{N} \left(\left| P_i - \overline{O} \right| + \left| O_i - \overline{O} \right| \right)^2} \quad (6)$$

where P_i and O_i represent ith predicted and observed values, respectively, $\overline{O}$ the mean observed values, and N the sample size. R^2 measures the goodness-of-fit of a linear relationship between simulated and observed values, and hence ignores model bias. R^2 is also sensitive to the variance of the samples. *RMSE* and *NRMSE* represent the mean difference of predictions and observations, and they include measures of both bias and random errors. *EF* and *d* assess the degree of model prediction and are similar to R^2, except they are influenced by both bias and random errors. The index of agreement *d* is normalised by a measure of combined spread in observations and predictions, while *EF* (and R^2) are normalised by the spread in observations. The model reproduces experimental data perfectly when $R^2 = 1$, $RMSE = 0$, $NRMSE = 0$, $EF = 1$ and $d = 1$.

2.4. Description of reviewed datasets

Table 3 presents basic information on each paper validation datasets – location, reference, APSIM version, APSIM performance, and influential factors affecting the model performance. All reviewed works used APSIM Classic (version 1.X – version 7.9). The model has been applied mostly at plot or paddock, and sometimes regional, scales as a cropping system tool solely to assess the environmental impacts on food production, or combined with other models (e.g., climate projection models, economic models) to investigate future food security challenges and explore solutions or to develop profit maximisation strategies and study the effectiveness of crop insurance. A full version of Table 3 with detailed information is shown in Supplementary Table S2.

Overall, researchers report that site-specifically calibrated APSIM-Wheat provides a useful yield prediction tool for a wide range of environments. Nevertheless, while the model incorporates stress functions to account for limitations of water, nitrogen, heat and frost (Zheng et al., 2014)(), it sometimes fails to capture these stress effects sufficiently (Barlow et al., 2015). Each of the stress effects will be discussed in more detail in Section 3.

2.5. Building database for meta-analysis and performance metrics

All papers listed in Section 2.4 that had data that were extractable from tables, figures, text, or provided by the authors were included in the meta-database. In total, data from 30 studies were used to compose the meta-database for further analysis. These 30 studies are marked with asterisks in Table 3. Digitising the data from published scatter plots in the literature was performed with the WebPlotDigitizer tool (https://automeris.io/WebPlotDigitizer/). The database includes 1895 pairs of observed and simulated grain yields expressed in tons per ha. All these points were for validation simulations. The data originated from seven countries and included 51 wheat cultivars (see Table 3). These data were assembled and categorised according to different crop stresses and model initialisations. The conditions captured were:

- Crop stresses: water availability, nitrogen availability, heat stress, lodging, disease.
- Model initialisations: fully site-specific calibration, partially site-specific calibration, non-site-specific calibration.

APSIM Classic (model version please refer to Table 3) performance was evaluated for the whole data set and subsets corresponding to various conditions using the performance metrics in 2.3. To obtain R^2, a linear regression was fitted to the observed and simulated grain yield pairs. Residuals (simulated – observed yield) were also calculated and box plots drawn for different conditions. Comparisons between predicted yield residuals and observed yields were also plotted to visually investigate model capability and limitations. Statistics of coefficient of determination (R^2), *RMSE* (eq. 3), *NRMSE* (eq. 4), and *EF* (eq. 5) were utilised to quantify the model performance.

3. Factors affecting APSIM yield prediction

Several factors affecting APSIM-Wheat yield prediction were distilled and presented in the following section after all papers in Table 3 were reviewed and the meta-database composed with 30 papers was analysed (Section 2.5). Identified influencing factors include model calibration, crop resources (water, nitrogen), temperature and other biotic or abiotic stresses.

Overall, the model performed well. Fig. 2 compares the predicted yield with the observed yield from the meta-database. APSIM-Wheat predicted grain yield with $R^2 = 0.68$, $RMSE = 1.06$ t/ha, $NRMSE = 28.89\%$, $EF = 0.63$. This result is consistent with the findings from most papers reviewed in Section 2. To put these results in context of practical cropping decisions, Yield Prophet® users reported that discrepancies between the predicted and observed yields exceeding 0.5 t/ha reduced their confidence in using the model for decision support (Hochman et al., 2009a), indicating that factors contributing to the uncertainty and potential solutions should be explored. The deviation of observed vs. simulated yields scatters from the 1:1 line in Fig. 2 (black dashed line) denotes model simulation deficiencies. The discrepancy between the regression line (grey dashed line) and the 1:1 line indicates existence of bias that varies from positive to negative values with yield. Potential causes of this bias include not fully site-specific calibration, water stress, nitrogen stress, heat stress, lodging, root-lesion nematode. The variation of yield prediction error and uncertainty under different environments, treatments, and model initialisations will be analysed in the following sections separately.

3.1. Model calibration

APSIM-Wheat performs optimally when reliable and accurate soil information is available and biotic/abiotic stresses are absent (Dalgliesh et al., 2012). Accurate specification of soil water holding characteristics affects APSIM-Wheat prediction performance (Lilley et al., 2003; Sadras et al., 2003). Specifying lower limits of plant available water with field measurements rather than using estimations from soil texture can improve simulation accuracy. In one study, the R^2 of the relationship between simulated and observed yields increased from 0.60 to 0.74, and the RMSE decreased from 0.31 t/ha to 0.19 t/ha when using lower limits of extractable water derived from field gravimetric soil water measurements, compared with texture based estimates (Sadras et al., 2003). Hunt et al. (2006) indicated that when the model was initialised with appropriate soil water holding characteristics and input data, 68% of the yield predictions were within ±0.5 t/ha of the observed yields.

Fig. 3 shows APSIM-Wheat validation results of the studies that used site-specific calibration. As described in Section 2.3, site-specific calibration is done by (1) manually tuning parameters to make the simulations correspond well with the observations or (2) specifying parameters with field measurements (usually soil texture, soil hydraulic and/or chemical parameters. The results indicated that the model, once site-specifically calibrated ((1), (2) individually or simultaneously), was able to estimate the harvest yield with an R^2 of 0.90, $RMSE = 0.64$ t/ha, and a *NRMSE* of 14.08%. The model performance improved when model cultivar parameters were manually tuned and soil parameters were initialised with ground observations simultaneously (fully site-specific calibration), resulting in *RMSE* smaller than 0.5 t/ha, *NRMSE* of 10.15%, and an *EF* of 0.85, indicating that the model is performing well. When only the cultivar parameters were calibrated, the model maintained the *EF* of 0.8, with *RMSE* and *NRMSE* slightly increased to 0.7 t/ha and 12.93%, and an R^2 of 0.82. The yield prediction performance began to decline when only the soil parameters were specified with field

Table 3
List of validation datasets from the literature used in this study.

Country	Region	Reference	APSIM version	APSIM performance	Influential factor
Australia	Western Australia	(Asseng et al., 2004, 2002, 2001, 1998b, 1998a; Bell et al., 2009*; Bryan et al., 2014*; Fisher et al., 2001; Fletcher et al., 2020*; Lawes et al., 2009; Oliver et al., 2006*, 2009; Oliver and Robertson, 2009; Wang et al., 2003*; Wong and Asseng, 2006)	NWheat, 5.2, 5.4, 7.3, 7.8, N/A	Yield-RMSE = 0.31 to 1.2 t/ha Yield-R^2 = 0.69 to 0.86 Biomass-RMSE = 0.8 to 2.8 t/ha Biomass-R^2 = 0.80 to 0.94 LAI-RMSE = 0.6 to 1.3 LAI-R^2 = 0.53 to 0.73	Model calibration (Hunt et al., 2006; Lilley et al., 2003; Sadras et al., 2003) Soil cracking (Paydar et al., 2005) Water stress (Fletcher et al., 2020; Peake et al., 2014; Zeleke and Nendel, 2016)
	Queensland	(Bell et al., 2009*; Hochman et al., 2007; Mielenz et al., 2016*; O'Leary et al., 2016*; Peake et al., 2014*; Probert et al., 1998, 1995; Wang et al., 2003*)	1.X, 5.0, 5.4, 7.4, 7.5, 7.6, N/A	Yield-RMSE = 0.50 to 1.62 t/ha Yield-R^2 = 0.30 to 0.92	Nitrogen stress (Peake et al., 2014)
	New South Wales	(Bryan et al., 2014*; Hochman et al., 2007; Innes et al., 2015; Lilley et al., 2003; Lilley and Kirkegaard, 2008*; O'Leary et al., 2016*; Paydar et al., 2005*; Zeleke and Nendel, 2016*)	2.1, 5.0, 7.3, 7.5, 7.6, N/A	Yield-RMSE = 0.40 to 1.39 t/ha Yield-NRMSE = 18.9% (Innes et al., 2015) Yield-R^2 = 0.69 to 0.92	Heat stress (Hochman et al., 2009a; Peake et al., 2014) Lodging (Peake et al., 2014)
	Victoria	(Anwar et al., 2009; Bryan et al., 2014*; Hochman et al., 2013; O'Leary et al., 2015; Sadras et al., 2003*)	5.3, 7.3, 7.4, N/A	Yield-RMSE = 0.19 to 1.29 t/ha Yyield-R^2 = 0.6 to 0.96	Root-lesion nematode (O'Leary et al., 2016; Probert et al., 1995)
	South Australia	(Bryan et al., 2014*; Luo et al., 2005; Yunusa et al., 2004)	1.4 Patch 2, 2.0, 7.3	Yield-RMSE = 0.45 t/ha Yield-R^2 = 0.69 Yield-residuals = ~0.4 t/ha	Subsoil constraints (Hochman et al., 2007)
	Tasmania	(Acuña et al., 2015; Phelan et al., 2018*)	7.1, 7.8	Yield-RMSE = 1 t/ha Yield-R^2 = 0.83 to 0.84 Yield-EF = 0.82	
Australia assembled data		(Carberry et al., 2013, 2009; Hochman et al., 2009a; Hunt et al., 2006*)	Yield Prophet	Yield-RMSE = 0.19 to 0.80 t/ha Yield-R^2 = 0.52 to 0.89	
New Zealand	Lincoln	(Asseng et al., 2004; Bell et al., 2009*)	NWheat, 5.4	Yield-RMSE = 0.5 to 1.2 t/ha Yield-NRMSE = ~18% Yield-R^2 = 0.72 to 0.77 Biomass-RMSE = 1.1 to 2.8 t/ha Biomass-NRMSE = ~17% Biomass-R^2 = 0.86 to 0.94 LAI-RMSE = 0.9 to 1.3 LAI-R^2 = 0.53 to 0.73	
China	North China Plain, Loess Plateau, Gongzhuling, Ürümqi, Zhengzhou, Xuzhou, Inner Mongolia	(Bai et al., 2020; Chen et al., 2010c*, 2010b*, 2010a*; He et al., 2014; Li et al., 2016, 2014; Liu et al., 2016a*; Sun et al., 2015; Van Oort et al., 2016; Wang et al., 2009*, 2014*, 2013*; Xiao and Tao, 2014*; Yan et al., 2020*; Zhang et al., 2013*, 2012*; Zhao et al., 2017*, Zhao et al., 2015*, 2014a, b*)	5.1, 5.3, 6.1, 7.0, 7.4, 7.5, N/A	Yield-RMSE = 0.29 to 1.26 t/ha Yield-NRMSE = 7% to 22% Yield-R^2 = 0.46 to 0.97 Yield-d = 0.85 to 0.97 Biomass-RMSE = 0.88 to 1.4 t/ha Biomass-R^2 = 0.62 to 0.91	Model calibration (Zhao et al., 2014b) Water stress (Balwinder-Singh et al., 2011; Deihimfard et al., 2015) Nitrogen stress (Zhao et al., 2014a)
India	Punjab, Indo-Gangetic Plains, Bhopal	(Balwinder-Singh et al., 2011*; Lobell et al., 2012; Mohanty et al., 2012)	5.1, 6.0, N/A	Yield-RMSE = 0.44 to 0.55 t/ha Yield-NRMSE = 12.4% to 16.5% Yield-R^2 = 0.86 to 0.91 Biomass-RMSE = 0.3 to 0.8 t/ha Biomass-NRMSE = 3.6% to 10.8% Biomass-R^2 = 0.92 to 0.99 (Balwinder-Singh et al., 2011)	Heat stress (Hussain et al., 2018; Liu et al., 2016a; Lobell et al., 2012; Zhang et al., 2012) Frost stress (Chen et al., 2010b, 2010c; Wang et al., 2009; Zhang et al., 2013, 2012)
Iran	Grogan region and Khorasan province	(Deihimfard et al., 2015*; Soltani and Sinclair, 2015)	7.X, 7.2	Yield-RMSE = 0.62 to 0.71 t/ha Yield-R^2 = 0.81 to 0.83	Soil cracking (Moeller et al., 2007; Mohanty et al., 2012)
Syria	Dry areas at Tel Hadya, north-western Syria	(Moeller et al., 2007)	4.2	At pre-anthesis stage, the model overestimated leaf-area, nitrogen uptake and biomass accumulation (Moeller et al., 2007).	
Pakistan	Islamabad; Faisalabad and Layyah in Punjab-Pakistan	(Ahmed et al., 2016; Hussain et al., 2018)	7.8, N/A	Phenology-RMSE = 2.0 to 5.1 days Phenology-R^2 = 0.8 LAI-RMSE = 0.14 to 0.32 LAI-R^2 = 0.83 Biomass-RMSE = 0.15 to 0.40 t/ha Biomass-R^2 = 0.92	

(*continued on next page*)

Table 3 (*continued*)

Country	Region	Reference	APSIM version	APSIM performance	Influential factor
				Yield-RMSE = 0.12 to 0.31 t/ha Yield- R^2 = 0.82 (Ahmed et al., 2016) The model overestimated yield with late planting dates (Hussain et al., 2018).	
Asia assembled data (Twelve Asian countries, total of 43 experimental datasets, 966 crops, 326 of them were wheat)		(Gaydon et al., 2017)*	Multiple versions	Yield-RMSE = 0.845 t/ha Yield-R^2 = 0.79 Yield-standard deviation = 1.794 t/ha APSIM underestimated LAI, biomass, and yield in NCP, China due to incorrect temperature response of physiological processes.	
Ethiopia	Northern Ethiopia	(Araya et al., 2020*, 2017)	7.4, 7.7	Yield-NRMSE = 7.7% to 22.8% Yield-R^2 = 0.63 Days of flowering-NRMSE = 3.1% to 4.3% Days of flowering-R^2 = 0.91 Days of maturity-NRMSE = 7.5% to 8.3% Days of maturity-R^2 = 0.81	
Tunisia	semiarid (Kef) and sub-humid (Bizerte)	(Bahri et al., 2019)	N/A	Yield-RMSE = 1.647 t/ha Yield-d = 0.83 (Bahri et al., 2019)	
The Netherlands, Australia, Belgium, China, Ethiopia, Iran, New Zealand, Turkey, United States of America		(Asseng et al., 2000; Brown et al., 2018, 2014; Holzworth et al., 2018, 2014)	Multiple versions	Yield-RMSE = 0.46 to 1 t/ha Yield-R^2 = 0.84 to 0.93 More validation results can be found in the model fields.	

* Data were used to compose the meta-database for further analysis in Section 3.

measurements without adjusting other model parameters, both R^2 and *EF* decreased to 0.77, with an *NRMSE* = 20.82%. The *RMSE* was only 0.51 t/ha since the yield range in this case were lower than in other cases.

Across the Australian dryland cropping area, the crucial challenge for predicting commercial wheat yield is to accurately describe the soil characteristics, soil water and nitrogen sources (Carberry et al., 2009). This requirement motivated the development of the APSoil soil database (Dalgliesh et al., 2012, 2009), which provides representative soil parameters for major Australian soils. For Australian paddocks, if field measured soil parameters are not available, APSoil can provide soil information such as the Plant Available Water Capacity (PAWC) based on approximate soil type information (Innes et al., 2015; Phelan et al., 2018).

Fig. 4 shows results when soil parameters were specified using a soil database – APSoil or estimated soil hydraulic characteristics. Model default genotype parameters were utilised for specific cultivars. Compared to cases in Fig. 3, these initialisation methods led to decrease the model accuracy and uncertainty, resulting in *RMSE* increasing from 0.64 to 1.25 t/ha and *NRMSE* increasing from 14.0% to 32.46%. When estimated soil hydraulic parameters were used, the *RMSE* of yield prediction was 1.37 t/ha and the *NRMSE* was 40.45%. Performance improved using the APSoil database to specify soil parameters resulting in model predictions with lower *RMSE* and *NRMSE* of 0.7 t/ha and 13.0%, compared with the model performance when using soil texture-derived soil parameters.

Results in Fig. 3 and Fig. 4 indicate that manually tuning cultivar parameters, and/or specifying the soil characteristics with ground observations can substantially improve the model performance. Convincing evidence is presented to demonstrate that APSIM-Wheat is able to simulate wheat grain yield within 0.5 t/ha when fully site-specific calibration implemented. When field measured data is not available, using a look-up-table approach that uses APSoil to specify the soil hydraulic properties can achieve yield prediction accuracy of *RMSE* = 0.7 t/ha. Setting soil parameters with estimated data is still acceptable, but not ideal. The estimated soil parameters largely affect the yield prediction accuracy and uncertainty since they cannot appropriately describe the soil properties.

Some other parameters and functions in APSIM have been modified by authors to achieve better performance. The maximum and critical nitrogen concentration in leaves used in the APSIM-Wheat model was too low when compared to the observed data collected from North China Plain (NCP) fields. Adjustment of these two parameters can improve the model simulation, especially under low nitrogen input (Zhao et al., 2014a). Root growth parameters were modified to better simulate the root biomass and its distribution (Zhao et al., 2015, 2014b). The soil moisture factor used for the denitrification rate calculation was modified by Mielenz et al. (2016), instead of using drained upper limit (DUL) as the threshold, the authors modified it to be decided by the water-filled pore space and saturation (SAT). Brown et al. (2018) pointed out that the phenology model needs careful parametrisation for different cultivars.

3.2. *Water availability*

To assess the impacts of water availability on APSIM yield prediction, only site-specifically calibrated datasets from irrigated or water limited fields have been selected. Fig. 5 shows box plots of prediction residuals. The cases are presented in the order of water stress, from highest (1) to lowest (3). Case 1 shows datasets for crops under water limited conditions. Datasets from two papers were included (Fletcher et al., 2020; Peake et al., 2014). Wheat from Case 2 was irrigated at critical growth stages with different amounts of water (Balwinder-Singh et al., 2011; Chen et al., 2010b; Deihimfard et al., 2015; Wang et al., 2013; Xiao and Tao, 2014; Yan et al., 2020; Zhang et al., 2013; Zhao et al., 2014b). Wheat from Case 3 was also irrigated, but not at specific

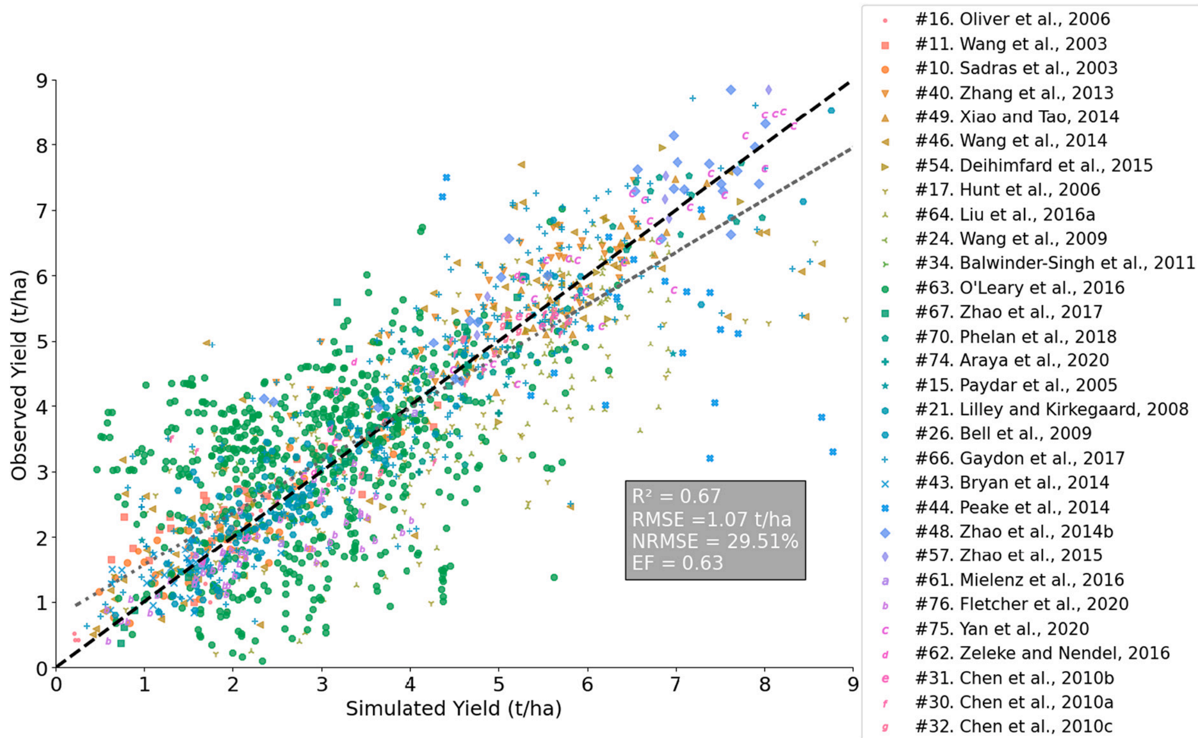

Fig. 2. Comparison between observed and APSIM-Wheat simulated grain yields (black dashed line: 1:1 line; grey dashed line: regression line).

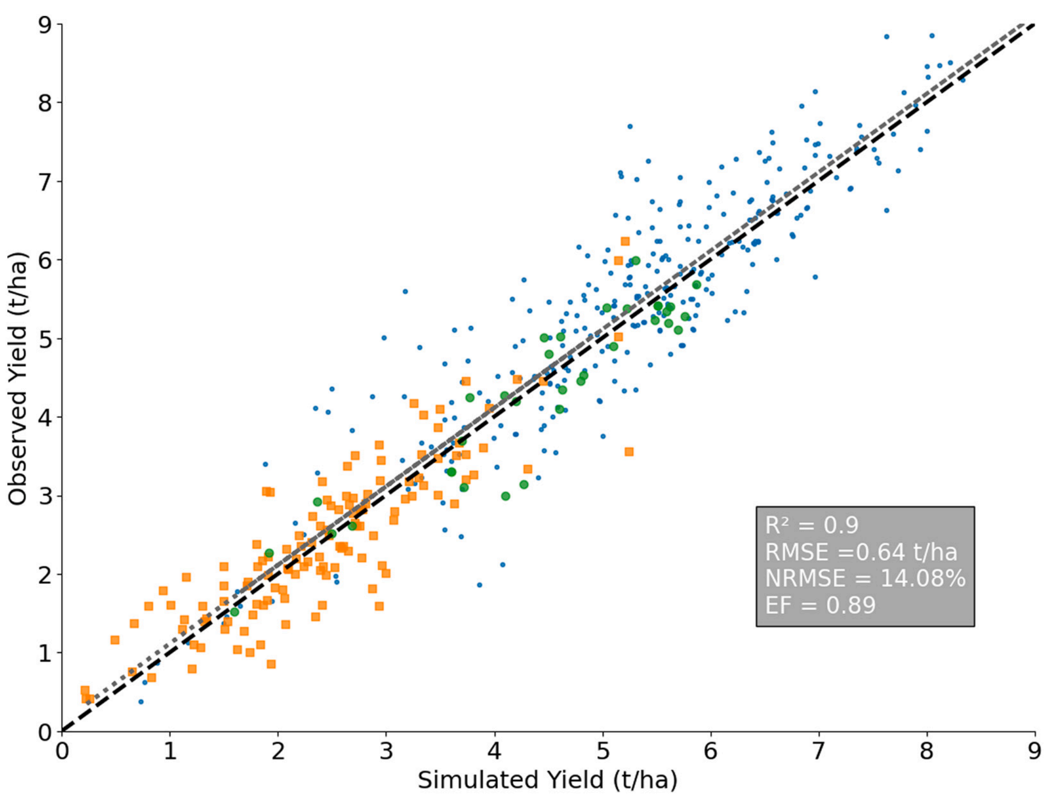

Fig. 3. Comparison between observed and APSIM-Wheat simulated grain yields when cultivar parameters were manually tuned, and/or soil parameters were specified with ground observations (green circle: both cultivar and soil parameters were calibrated, R^2 = 0.87, RMSE = 0.44 t/ha, NRMSE = 10.15%, EF = 0.85; blue dot: only cultivar parameters were tuned, R^2 = 0.82, RMSE = 0.7 t/ha, NRMSE = 12.93%, EF = 0.8; orange square: only soil parameters were specified using field measurements, R^2 = 0.77, RMSE = 0.51 t/ha, NRMSE = 20.82%, EF = 0.77). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

growth stages. The irrigation amount and scheduling were adapted to the actual water demand (Gaydon et al., 2017; Mielenz et al., 2016; Yan et al., 2020).

Wheat in Case 1 suffered from water stress. Peake et al. (2014) observed mild water stress during the pre- and post-anthesis, while the model was also used to predict water-limited yield (Fletcher et al., 2020). 50% of the predicted yield residuals were within the range of 0.2–1 t/ha, 99.3% of them were within the range − 0.4–2.4 t/ha, while the median was approximately 0.33 t/ha. From the datasets we analysed, yield overestimation was more obvious than underestimation

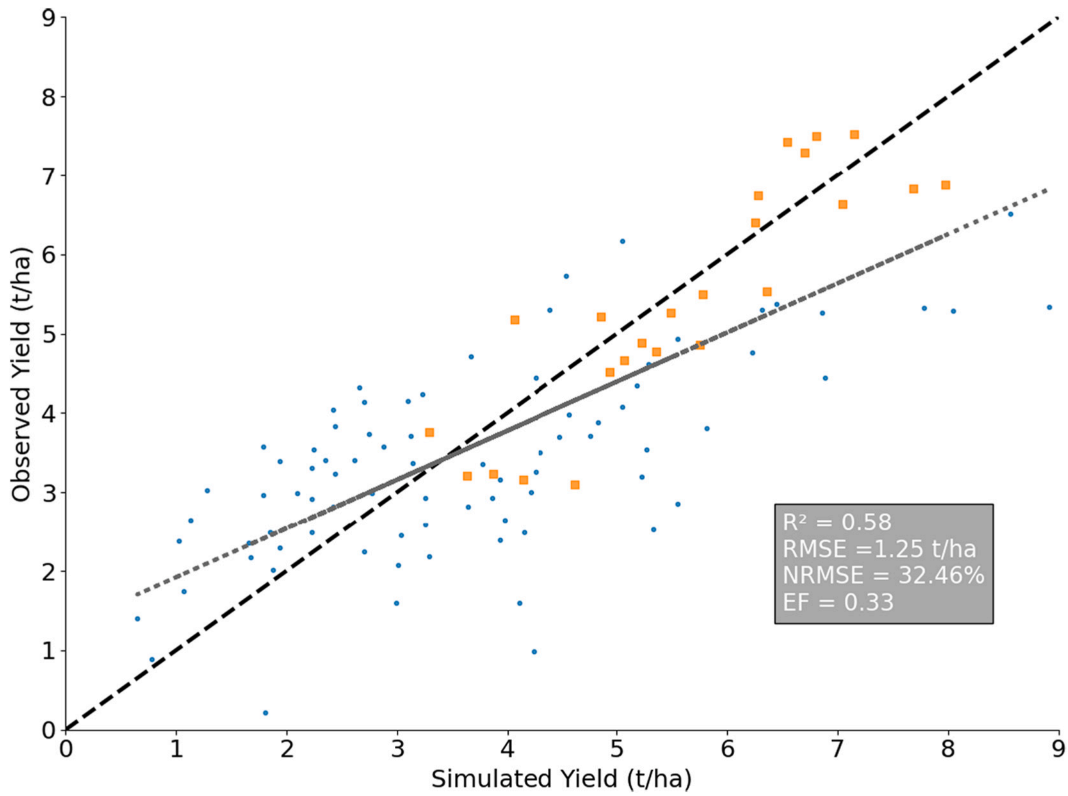

Fig. 4. Comparison between observed and APSIM-Wheat simulated grain yields when soil parameters specified using APSoil or estimated data (blue dot: estimated soil characteristics, $R^2 = 0.45$, RMSE = 1.37 t/ha, NRMSE = 40.45%, EF = -0.27; orange square: soil parameters were specified using APSoil, $R^2 = 0.78$, RMSE = 0.7 t/ha, NRMSE = 13.0%, EF = 0.76). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

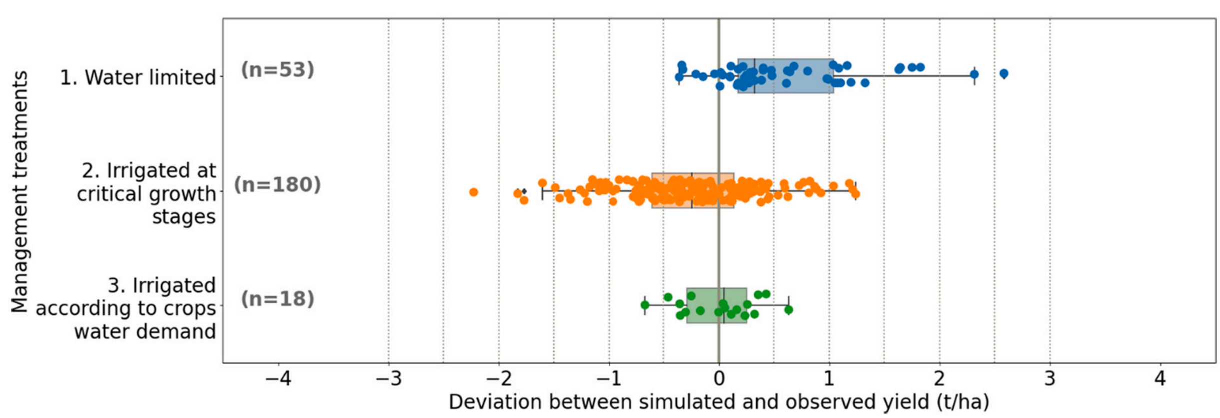

Fig. 5. Boxplot of APSIM predicted yield residuals under different irrigation practices.

under water stressed conditions. In Case 2, the fields were mainly from Punjab, India, NCP, China, and North-eastern Iran. They were irrigated at critical growth stages, e.g., sowing, jointing, flowering, and grain filling, with total irrigation amounts between 75 and 450 mm. The accuracy of modelled yields was acceptable with *RMSE* around 0.65 t/ha. The median of residuals of modelled yields did not exceed −0.5 t/ha. Approximately 50% of the predicted yield residuals were within the range of −0.65–0.15 t/ha, and 99.3% of them were within the range of −1.7–1.25 t/ha. Underestimation was more obvious than overestimation. The model was examined by Balwinder-Singh et al. (2011) in India for six irrigation scheduling treatments. The results indicated that it underpredicted grain yield by 0.6–1 t/ha when crops were subject to water deficit. Case 3 shows crops irrigated according to their water demand. Irrigation scheduling and amount were adjusted according to rainfall amount, soil water content, and crop requirement. Crops in this case barely experienced water limitation and the model performance was more accurate and stable. The residual medians were less than 0.2 t/ha, and 99.3% of the residuals were within ±0.7 t/ha.

Case 1 demonstrated that APSIM-Wheat tend to overestimate yield with more significant uncertainty under water-limited conditions. It seems that the constraint on wheat growth by limited water is not well accounted for by APSIM-Wheat, leading to overly optimistic grain yield prediction. The mechanism that APSIM-Wheat uses to handle water stress was described in Section 2.1. The model only accounts for water deficit impacts on biomass production and leaf expansion. It does include a function intended to account for water stress on phenology, but the default parameterisation results in no effect on phenology. Consequently, proper parametrisation to correctly estimate drought impact on phenology under water-limited condition is needed. For example, Chauhan et al. (2019) accounted for soil water effect to modulate APSIM Classic (version 7.10) predicted flowering time. But the proposed method can only reduce the daily thermal time and delay the flowering time when the soil water is sufficient (fractional available soil water>0.65). A proper scheme to directly simulate the impact of soil water stress on flowering time is yet to be developed. Greater water limitations result in higher canopy temperatures, which reduce the duration of biomass accumulation. The increased canopy temperatures under water deficit conditions should be considered to improve the performance of yield prediction (Asseng et al., 2004). Asseng et al. (1998b) also attributed the underpredicted yield to insufficient re-translocation of stored pre-anthesis carbohydrates to the grain by APSIM. They suggested the model can be improved by including functions to remobilise additional carbohydrates of stem into the grain when crops experience severe drought conditions. Case 2 showed that with critical-stage irrigation the model can predict yield with acceptable accuracy ($RMSE$ = 0.65 t/ha), while the uncertainty is still obvious. These datasets demonstrated that once extra water was supplied (in addition to rainfall), APSIM-Wheat could capture the additional water resource. Case 3 showed that supplying irrigation water according to crop demand to avoid water limitation was associated with better modelling performance.

Users operating APSIM in a water-limited situation should be aware of uncertainty and possible yield overestimation. Most researchers validate the model using real-world datasets to create confidence in its performance before using it in combination with climate projections for predicting food production under climate change scenarios. The frequency and intensity of droughts are projected to increase (Zhou et al., 2019) and the water availability for rain-fed agriculture is decreasing, and the crop model will probably underestimate yields under those conditions. Larger prediction uncertainty should be considered when utilising cropping system as a tool to assess future food production and security.

3.3. Nitrogen availability

We selected site-specific calibrated datasets to assess the impacts of nitrogen availability on APSIM yield prediction, in the absence of other stresses. Fig. 6 shows box plots of prediction residuals of six cases, which were ordered from the largest to the smallest nitrogen stress. Case 1 shows datasets when crops experience nitrogen limitation. Datasets from two papers were included (Peake et al., 2014; Wang et al., 2014). Case 2 was also composed of datasets from two papers (Sadras et al., 2003; Zhao et al., 2014b). The authors did not specify the nitrogen rate in these datasets but declared no nitrogen stress was observed. Wheat from Cases 3–6 was fertilised with different rates of nitrogen. The application amount increased from 64 kg N/ha to 195 kg N/ha. Data for Case 3 were collected from three papers (Araya et al., 2020; Paydar et al., 2005; Phelan et al., 2018), while Cases 4–6 used datasets from Xiao and Tao (2014) and Yan et al. (2020).

Case 1 reported nitrogen stress symptoms (leaf yellowing) at DC31 (early stem elongation) (Peake et al., 2014), while the model was also used to predict yield when no fertiliser was applied in fields (Wang et al., 2014). Both overestimation and underestimation were observed with the median of residuals approximately −0.3 t/ha. In some cases, the underestimation was even more than 3 t/ha. Case 2 collected datasets with not specified fertilisation amounts, but no nitrogen stress was observed in the fields. The model predicted yield with acceptable accuracy and uncertainty. The median of residuals was close to zero. 50% of the predicted yield residuals were within the range of −0.5–0.2 t/ha, and 99.3% of them were within the range of −1.25–1 t/ha. Case 3 contained datasets with nitrogen rates of 64, 75, 100, and 128 kg N/ha. The distribution of the prediction residuals was similar to those in Case 2. With the increasing nitrogen application rate, the predicted yield residuals were less scattered, ranging within ±1.0 t/ha to ±0.5 t/ha while the medians tended towards 0 t/ha. The model was well-performed to catch the fertilisation differences.

Under nitrogen limited conditions (Case 1), APSIM-Wheat showed the largest uncertainties and more severe yield underestimation and the model tended to underestimate yield when crops suffered from nitrogen limitation. The reason as indicated by Peake et al. (2014) is that APSIM-Wheat overrated the nitrogen stress duration by two weeks longer compared to observed nitrogen stress in the paddocks. Cases 2–6 showed that once extra nitrogen was supplied, the model captured the increasing trend and tended to predict yield with better accuracy and lower uncertainty. The residuals were contained within ±1.0 t/ha when sufficient nitrogen was applied.

An additional parametrisation of the nitrogen impacts on phenology would be able to better address potential simulation problems. Zhao et al. (2014a) assessed the nitrogen concentration parameters used in the model, the results indicated that the higher leaf maximum and critical nitrogen concentrations led the model to overrate the nitrogen stress impacts on biomass accumulation and underrate the impacts on leaf expansion. They suggested to adjust and verify these parameters to increase the prediction accuracy of the model for grain yield.

3.4. Other stresses

Fig. 7 illustrates the model predicted yield residuals against the observed yield for datasets under irrigated and fertilised conditions. We intentionally included datasets for wheat without stress and under some abiotic stresses such as heat and lodging, to compare the model performance under stressed and stress-free situations (Deihimfard et al., 2015; Liu et al., 2016b; Mielenz et al., 2016; Peake et al., 2014; Xiao and Tao, 2014; Yan et al., 2020; Zeleke and Nendel, 2016; Zhao et al., 2015, 2014b). The model showed a good performance for all stress-free cases, with $RMSE$ = 0.66 t/ha and $NRMSE$ = 12.49%. However, when the

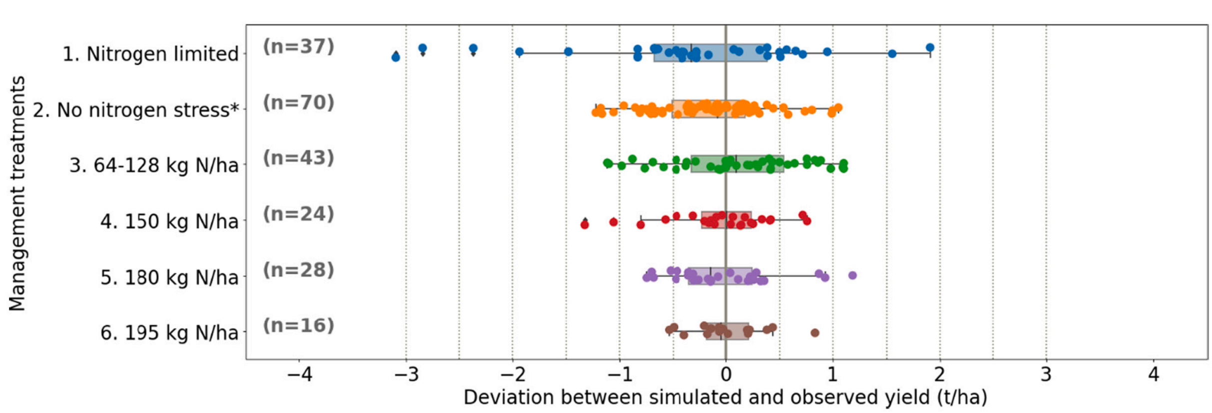

Fig. 6. Boxplot of APSIM predicted yield residuals under different nitrogen application rates (* fertiliser amount was not specified).

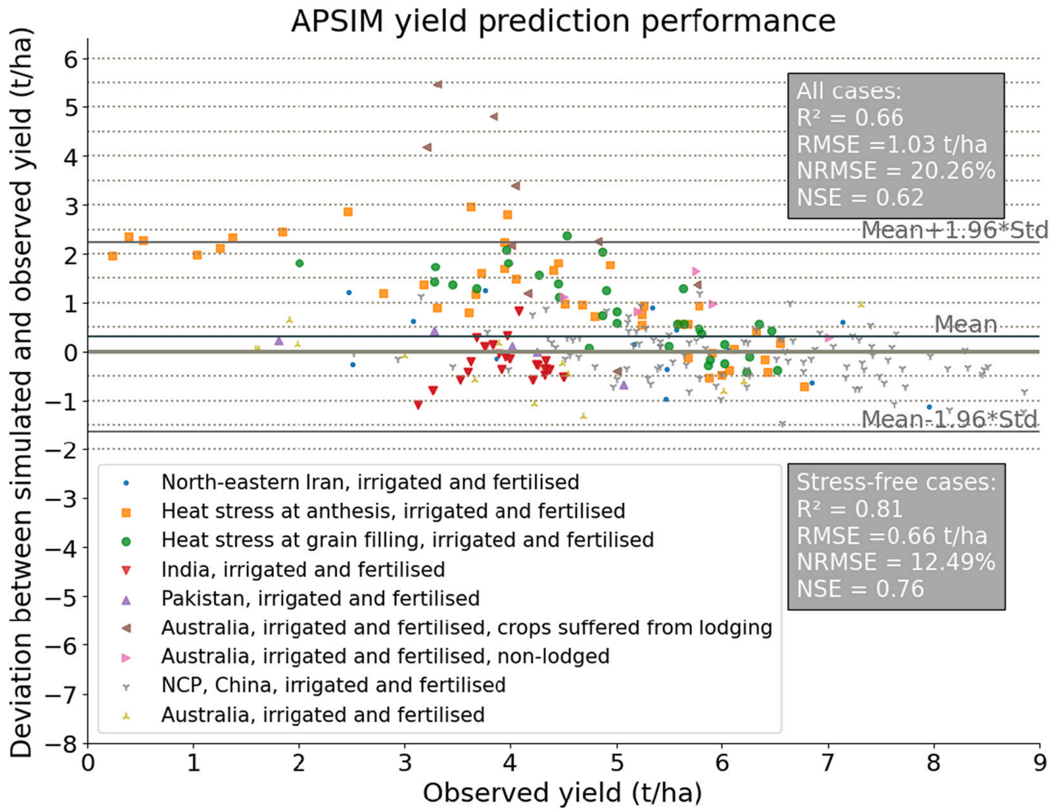

Fig. 7. Comparison between predicted yield residuals and observed yield under irrigated and fertilised condition.

stressed cases are included, *RMSE* increased to around 1.03 t/ha and *NRMSE* to 20.26%, respectively. The mean residual is 0.3 t/ha and standard deviation is 0.99 t/ha. Most of the residuals are between the range of ± 1.96 times of the standard deviation around the mean. The outliers are from the cases where the crops were under heat stress and impacted by lodging.

Heat stress. Heat stress during wheat growth, especially at anthesis and grain filling stages, affects APSIM yield prediction significantly (Liu et al., 2016a). Hochman et al., 2009a reported that a widespread unseasonal heatwave, followed by a frost in the Wimmera and Mallee regions of Victoria, Australia in 2004 caused the model to overestimate yields by 0.9 t/ha with a mean simulated yield of 1.8 t/ha. Lobell et al. (2012) found that the shortening of the green season (by +2 °C warming) was underrated by APSIM by up to eight days, and yield losses were underestimated by up to 50% after comparing the model simulation with a regression model based on nine years of wheat phenology (from satellite observations) and daily temperature data. Liu et al. (2016a) conducted environment-controlled chamber experiments to test the model response when heat stress happened at anthesis and grain filling stages. Wheat is more sensitive to heat at anthesis (orange squares in Fig. 7) with *RMSE* = 1.5 t/ha and *NRMSE* = 35.47% since both grain number and size are affected, while heat during grain filling (green circles in Fig. 7) only decreased the grain size, due to a shorter grain filling duration, resulting in *RMSE* = 1.14 t/ha and *NRMSE* = 22.75%. Barlow et al. (2015) also emphasised the need to define response functions for calculating extreme temperatures impacts, with a priority on the response during anthesis and grain filling stages. Hussain et al. (2018) evaluated performance of APSIM simulations of winter wheat sown at different times, from early to extremely late. The model poorly predicted yield for late planting dates due to high temperature during grain filling. Even a short-term exposure of wheat to extreme high temperatures at early grain filling can reduce the duration of grain filling and hence the cumulative degree days and resulting in smaller harvest yield (Stone and Nicolas, 1995). Lobell et al. (2012) also detected greater senescence from extreme heat, beyond the impacts of increased average temperatures.

In summary, the quality of grain number and size simulation exerts a critical influence on the accuracy of yield prediction. Only using the daily mean temperature to apply heat stress is not effective in accounting for heat wave impacts. In addition, short periods (1–3 days) of extremely high temperatures (> 33 °C) can also affect the crop growth and ultimately result in a significant reduction in grain yield (Barlow et al., 2015). Accounting for high daily maximum temperatures as another variable to determine the heat stress impact would help the model better respond to heat waves.

Frost damage. Barlow et al. (2015) summarised three crucial physiological damages that have impacts on yield production in response to a frost event: seedling death during the vegetative stage, sterility at anthesis and death of formed grains during grain filling. Frost during the vegetative stage has smaller impact on harvest yield than during later stages as it mainly affects seedling survival (Fuller et al., 2007) and causes leaf senescence (Shroyer et al., 1995). The greatest yield production impacts resulting from frost are at the reproductive stage, and this frost sensitivity increases from heading to the end of anthesis (Frederiks et al., 2012).

Hochman et al. (2013) found that the APSIM-Wheat (with the model default frost parameters) could not account for extreme events such as severe frosts and might overestimate harvest yields under those conditions, based on an assessment of the model with data collected from the Wimmera region of Victoria, Australia. In 1998 the crops on one farm of this region were severely damaged by stem frost and the model overestimated the harvest yield by more than 5 t/ha. Hochman et al., 2009a also reported an occurrence of both frost and heat damages in October 2004, late anthesis or early grain filling stages (the period when the crops are sensitive to extreme temperatures) in the Wimmera and Mallee regions of Victoria that caused the model to over-predict yield. For varieties with strong cold tolerance in the North China Plain, the minimum temperature threshold to cause leaf senescence was changed from

−15 °C to −20 °C to eliminate the underestimation of LAI, biomass and yield (Chen et al., 2010b; Wang et al., 2009; Zhang et al., 2013, 2012). The modified temperature response of thermal time calculation and the temperature response of radiation use efficiency (RUE) led to further improve model simulations (Chen et al., 2010b, 2010c).

Lodging. The brown triangular points from Fig. 7 represent the model predicted residuals against the observed yield when crops were impacted by lodging (the data is from Peake et al. (2014)). Yield is severely over-estimated with *RMSE* = 3.26 t/ha, *NRMSE* = 76.77%. The reviewed APSIM-Wheat version does not consider effects of crop lodging, while lodging can be caused by many factors, e.g., excessive nitrogen fertilisation and irrigation, heavy rain, wind, or hailstorm. The development of functions in APSIM-Wheat that accounts for the effects of lodging would be desirable although it would require collection of extensive databases of crops affected by lodging.

Other abiotic stresses. Some other factors APSIM-Wheat fails to simulate have been identified in model validation. The effect of soil cracking on soil evaporation is not taken into account in the reviewed model version, which leads the model to incorrectly simulate the water movement and further decreases yield prediction accuracy (Moeller et al., 2007; Mohanty et al., 2012; Paydar et al., 2005). Hochman et al. (2007) mentioned there was potential to improve yield prediction if a suitable function could be developed to describe the effects of subsoil constraints. When crops suffered hail damage in 1997 on one farm in the Wimmera region of Victoria, Australia, the model totally missed the hail storm damage and still predicted grain yield over 7 t/ha (Hochman et al., 2013). O'Leary et al. (2015) tested the APSIM-Wheat under two water regimes (irrigation and rain-fed), two nitrogen fertilisation regimes (0 and 53–138 kg N/ha), and two sowing dates for daytime ambient (365 μmol/mol) and elevated (550 μmol/mol) CO_2 environments at Horsham, Australia. The results indicated that the model showed a tendency to overestimate early biomass (DC31, stem elongation) (Zadoks et al., 1974), biomass at DC65 (anthesis), LAI at DC65 and grain yield under the normal CO_2 conditions; the resulting *RMSE* values were 1.592 t/ha, 1.542 t/ha, 0.70 m^2/m^2 and 1.294 t/ha, respectively. Under the elevated CO_2 condition, the model overcompensated the CO_2 effect and over predicted early biomass and harvest yields.

Biotic Stress. Crops in most of the reviewed papers were well managed, with no significant insects, weeds, pests, or plant diseases observed. O'Leary et al. (2016) examined the performance of the APSIM-Wheat model under different stubble, tillage and nitrogen application management scenarios. Some large predictive errors were found when the model predicted yields for fields of Warwick, Australia, where the wheat was heavily infected with the root-lesion nematode. Biotic stress such as root disease load can have major impacts that are not represented in APSIM-Wheat yet. The simulated yield deviated more from the observed (*RMSE* = 1.54 t/ha) when high nitrogen fertiliser was applied.

3.5. Implications of the influential factors in changing climate

Under future climate scenarios, both mean and variance of temperatures are projected to increase, along with precipitation variability. This will lead to increased heat waves, frost risk, and changing risk of drought and flood (Kundzewicz et al., 2014; Meehl et al., 2000; Perkins et al., 2012; Rigby and Porporato, 2008; Trenberth, 2011; Zeppel et al., 2014). The changing climate may also be favourable to certain wheat diseases, e.g. stripe rust (Luck et al., 2011) which have not been represented in the model yet. APSIM-Wheat, as a major cropping system tool used to study climate change impacts and seek solutions to address them (Deihimfard et al., 2018; Yang et al., 2014), needs improvement in the representation of heat stress, frost stress, water deficit, and the effects of pests, particularly when it is adopted to predict wheat production under the projected climate scenarios.

In addition to daily mean temperature, maximum temperature could be included as a variable to determine heat stress impact. The underestimation of heat stress impacts will lead to over-optimistic simulations of the future wheat production. Meanwhile, increasing mean temperatures accelerate crop growth and shorten the growing season, resulting in crops reaching the frost-sensitive anthesis stage more rapidly (Zheng et al., 2015). The absence of parameter values for functions to account for frosts can potentially lead to overestimation of harvest yields. Parameterising the frost damages of leaf senescence, seedling death, or death of formed grains will improve the model simulation capability. The variable precipitation intensity and probability may reduce users' confidence in simulation accuracy since the model showed uncertainty in predicting water-limited yield. Improved functioning and parametrisation to correctly estimate water deficit impacts on wheat growth is warranted. Apart from using the model to study future climate impacts on production, when users apply the model to a new study area or cultivar, accurate soil parameters and site-specifically calibrated cultivar parameters improve the model performance.

4. Summary and conclusion

In this work, we have reviewed 76 articles and conducted a meta-analysis of 30 applications of the APSIM model (APSIM Classic, version 1.X – version 7.9) to obtain detailed information on the process-based model's performance in predicting wheat yields. Our study shows that the model provides reasonably accurate wheat grain yields across a wide range of varieties, environments, and management practices around the world with an overall uncertainty of about 1 t/ha. However, we found a large variation in uncertainties within the modelling studies considered, especially between studies with site-specific calibration and non-site-specific calibration.

Furthermore, we found that factors such as heat and frost stress, water and nitrogen availability, soil parameterisation, calibration of genotype parameters, soil cracking, lodging, increased atmospheric CO_2 concentration and plant diseases are important factors affecting model performance. Heat and frost stresses, in particular, caused large discrepancies in the prediction of grain yield. One reason for this is that the reviewed model versions use only daily mean temperature as a heat factor to calculate the effects on biomass accumulation, although wheat is particularly sensitive to shorter-term heat stress during the anthesis and grain filling phases. Therefore, APSIM tended to overestimate crop yield that experienced heat wave conditions. Frost stress functions are already implemented in the reviewed model but without default parametrisation which negates their effect (impact factor = 0), so APSIM overestimates yield in crops subject to frost damage. The applications of APSIM to situations with water stress and nitrogen limitation led to greater uncertainties (overestimation for water stress and underestimation for nitrogen stress). Like the frost stress function, the effects of water and nitrogen stress on phenology are not yet parameterised.

A fully or partial site-specific calibration resulted in crop yields being predicted with higher accuracy (on average, *RMSE* and *NRMSE* were 0.64 t/ha and 14.08%, respectively). A fully site-specific calibration, including the determination of soil hydraulic parameters, initial soil conditions from field measurements and adjustment of other parameters (such as crop parameters), resulted in the lowest uncertainty in crop prediction (*RMSE* = 0.44 t/ha, *NRMSE* = 10.15%). If only soil parameters, and not cultivar parameters, are calibrated, the yield prediction accuracy slightly decreases, resulting in RMSE = 0.51 t/ha and NRMSE = 20.8%. This paper has summarised tuned cultivar parameters where available, with Table 2 lists the parameters and their calibrated value ranges and Supplementary Table S1 provides detailed parameter values reported by individual studies. These calibrated values reflect the effect of genetic differences under differing management or environmental scenarios. Future model users could start setting the parameters using values from Table S1 when calibrating identical cultivars and running the model under similar conditions. If soil parameters are not available, using a soil database such as APSoil to specify soil hydraulic properties is a good alternative, leading to yield predictions on average with *RMSE* = 0.7 t/ha and *NRMSE* = 13.0%. Soil texture-derived soil parameterisation is also acceptable but with comparatively lower accuracy and uncertainty with an $RMSE = 1.37$ t/ha and an $NRMSE = 40.45\%$.

The reviewed APSIM-Wheat version is not equipped with functions that account for other abiotic and biotic influences like soil cracking, lodging, or crop disease. Improving the model functionally to consider all these factors could lead to better crop predictions; however, a major challenge is that there is often a significant stochastic component to these influences. The most practical suggestions to reduce the errors in predicting would be (1) fully calibrating the model to local conditions by tuning soil and cultivar parameters; (2) developing a database sharing cultivar parameter sets which could help in specifying the genetic characteristics under various conditions, similar to the APSOIL database; and (3) applying frost-heat damage functions like Bell et al. (2015) developed to adjust grain yields when encountering temperature stresses. An alternative would be to pursue methods such as assimilating external observations into the model to continuously adjust certain model state variables and properties to improve model performance. Remote sensing data can provide timely information on the crop or environment status and could be used to update the model simulation regularly during the simulation. Another option is to use multi-model ensembles to account for model uncertainty in describing the impact of climate change on agricultural productivity (Asseng et al., 2015, 2013; Iizumi et al., 2018; Maiorano et al., 2017; Martre et al., 2015b; Wang et al., 2017).

This work did not assess the model's ability of simulating other crop states such as biomass, leaf area, water use, or fertility dynamics. The simulation quality of these dynamics is still largely unknown and worth further investigation.

The meta-database in this paper was composed of datasets from separate papers. In our meta-analysis, datasets from existing papers were compiled to analyse the impact of certain factors, while other factors could not be held constant, which may have led to some bias. The model validations considered in our study were all point-based, the plant models are usually used at the plot, field scales or even larger. However, the effects of spatial heterogeneity were not considered in our study. Finally, we did not consider the uncertainties embedded in the forcing inputs. According to Tao et al. (2018), when coupling climate models with crop models, the uncertainty from downscaled climate projections could be larger than those from crop models.

Crop models like APSIM are not just predictive tools, but also exploratory tools in conjunction with future scenarios. The vision for agricultural systems models is to accelerate progress of finding ways to address the global food security challenges. This paper aims to provide the perspectives on the model outputs credibility and uncertainty under various conditions covering a wide spectrum of management practices, environments, and wheat varieties. We expect that our analysis of APSIM-Wheat model performance will assist users to have appropriate interpretations and avoid misuse of the model.

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2021.103278.

Declaration of Competing Interest

The authors declare that this work has no known conflict of interests, competing financial interests, or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors would like to thank Garry J. O'Leary (Agriculture Victoria, Department of Jobs, Precincts and Regions) and Keith G. Pembleton (University of Southern Queensland) for providing valuable and insightful comments that improved the quality of this paper. We gratefully acknowledge Donald S. Gaydon (CSIRO Agriculture and Food, Australia), Peter J. Innes, Hamish E. Brown (New Zealand Institute for Plant and Food Research) and Neil I. Huth (CSIRO Agriculture and Food, Australia) for providing the datasets used in the evaluation of the model; Peter Carberry, Zvi Hochman, and Victor Sadras for friendly replies and suggestions. Harrie-Jan Hendricks Franssen acknowledges support from the Deutsche Forschungsgemeinschaft under Germany's Excellence Strategy, EXC-2070–390732324–PhenoRob. Acknowledgement is also made to the APSIM Initiative which takes responsibility for quality assurance and a structured innovation programme for APSIM's modelling software, which is provided free for research and development use (see www.apsim.info for details).

References

Acuña, T.B., Lisson, S., Johnson, P., Dean, G., 2015. Yield and water-use efficiency of wheat in a high-rainfall environment. Crop Pasture Sci. 66, 419–429.
Ahmed, M., Akram, M.N., Asim, M., Aslam, M., Ul Hassan, F., Higgins, S., Stöckle, C.O., Hoogenboom, G., 2016. Calibration and validation of APSIM-wheat and CERES-wheat for spring wheat under rainfed conditions: models evaluation and application. Comput. Electron. Agric. 123, 384–401. https://doi.org/10.1016/j.compag.2016.03.015.
Akinseye, F.M., Ajeigbe, H.A., Traore, P.C.S., Agele, S.O., Zemadim, B., Whitbread, A., 2020. Improving sorghum productivity under changing climatic conditions: a modelling approach. F. Crop. Res. 246, 107685.
Anwar, M.R., O'Leary, G.J., Rab, M.A., Fisher, P.D., Armstrong, R.D., 2009. Advances in precision agriculture in south-eastern Australia. V. Effect of seasonal conditions on wheat and barley yield response to applied nitrogen across management zones. Crop Pasture Sci. 60, 901–911.
Anwar, M.R., Wang, B., Li Liu, D., Waters, C., 2020. Late planting has great potential to mitigate the effects of future climate change on Australian rain-fed cotton. Sci. Total Environ. 714, 136806.
Araya, A., Kisekka, I., Girma, A., Hadgu, K.M., Tegebu, F.N., Kassa, A.H., Ferreira-Filho, H.R., Beltrao, N.E., Afewerk, A., Abadi, B., et al., 2017. The challenges and opportunities for wheat production under future climate in Northern Ethiopia. J. Agric. Sci. 155, 379–393.
Araya, A., Prasad, P.V.V., Gowda, P.H., Djanaguiraman, M., Kassa, A.H., 2020. Potential impacts of climate change factors and agronomic adaptation strategies on wheat yields in central highlands of Ethiopia. Clim. Chang. 1–19.
Archontoulis, S.V., Miguez, F.E., Moore, K.J., 2014. Evaluating APSIM maize, soil water, soil nitrogen, manure, and soil temperature modules in the Midwestern United States. Agron. J. 106, 1025–1040.
Asseng, S., Anderson, G.C., Dunin, F.X., Fillery, I.R.P., Dolling, P.J., Keating, B.A., 1998a. Use of the APSIM wheat model to predict yield, drainage, and NO3-leaching for a deep sand. Aust. J. Agric. Res. 49, 363–378.
Asseng, S., Keating, B.A., Fillery, I.R.P., Gregory, P.J., Bowden, J.W., Turner, N.C., Palta, J.A., Abrecht, D.G., 1998b. Performance of the APSIM-wheat model in Western Australia. F. Crop. Res. 57, 163–179.
Asseng, S., Van Keulen, H., Stol, W., 2000. Performance and application of the APSIM Nwheat model in the Netherlands. Eur. J. Agron. 12, 37–54.
Asseng, S., Turner, N.C., Keating, B.A., 2001. Analysis of water-and nitrogen-use efficiency of wheat in a Mediterranean climate. Plant Soil 233, 127–143.
Asseng, S., Bar-Tal, A., Bowden, J.W., Keating, B.A., Van Herwaarden, A., Palta, J.A., Huth, N.I., Probert, M.E., 2002. Simulation of grain protein content with APSIM-Nwheat. Eur. J. Agron. 16, 25–42.
Asseng, S., Jamieson, P.D., Kimball, B., Pinter, P., Sayre, K., Bowden, J.W., Howden, S. M., 2004. Simulated wheat growth affected by rising temperature, increased water deficit and elevated atmospheric CO2. F. Crop. Res. 85, 85–102. https://doi.org/10.1016/S0378-4290(03)00154-0.
Asseng, S., Foster, I.A.N., Turner, N.C., 2011. The impact of temperature variability on wheat yields. Glob. Chang. Biol. 17, 997–1012.
Asseng, S., Ewert, F., Rosenzweig, C., Jones, J.W., Hatfield, J.L., Ruane, A.C., Boote, K.J., Thorburn, P.J., Rötter, R.P., Cammarano, D., Brisson, N., Basso, B., Martre, P., Aggarwal, P.K., Angulo, C., Bertuzzi, P., Biernath, C., Challinor, A.J., Doltra, J., Gayler, S., Goldberg, R., Grant, R., Heng, L., Hooker, J., Hunt, L.A., Ingwersen, J., Izaurralde, R.C., Kersebaum, K.C., Müller, C., Naresh Kumar, S., Nendel, C., O'Leary, G., Olesen, J.E., Osborne, T.M., Palosuo, T., Priesack, E., Ripoche, D., Semenov, M.A., Shcherbak, I., Steduto, P., Stöckle, C., Stratonovitch, P., Streck, T., Supit, I., Tao, F., Travasso, M., Waha, K., Wallach, D., White, J.W., Williams, J.R., Wolf, J., 2013. Uncertainty in simulating wheat yields under climate change. Nat. Clim. Chang. 3, 827–832. https://doi.org/10.1038/nclimate1916.
Asseng, S., Ewert, F., Martre, P., Rötter, R.P., Lobell, D.B., Cammarano, D., Kimball, B.A., Ottman, M.J., Wall, G.W., White, J.W., Reynolds, M.P., Alderman, P.D., Prasad, P.V. V., Aggarwal, P.K., Anothai, J., Basso, B., Biernath, C., Challinor, A.J., De Sanctis, G., Doltra, J., Fereres, E., Garcia-Vila, M., Gayler, S., Hoogenboom, G., Hunt, L.A., Izaurralde, R.C., Jabloun, M., Jones, C.D., Kersebaum, K.C., Koehler, A.K., Müller, C., Naresh Kumar, S., Nendel, C., O'leary, G., Olesen, J.E., Palosuo, T., Priesack, E., Eyshi Rezaei, E., Ruane, A.C., Semenov, M.A., Shcherbak, I., Stöckle, C., Stratonovitch, P., Streck, T., Supit, I., Tao, F., Thorburn, P.J., Waha, K., Wang, E., Wallach, D., Wolf, J., Zhao, Z., Zhu, Y., 2015. Rising temperatures reduce global wheat production. Nat. Clim. Chang. 5, 143–147. https://doi.org/10.1038/nclimate2470.
Bahri, H., Annabi, M., M'Hamed, H.C., Frija, A., 2019. Assessing the long-term impact of conservation agriculture on wheat-based systems in Tunisia using APSIM simulations under a climate change context. Sci. Total Environ. 692, 1223–1233.

Bai, H., Wang, J., Fang, Q., Huang, B., 2020. Does a trade-off between yield and efficiency reduce water and nitrogen inputs of winter wheat in the North China Plain? Agric. Water Manag. 233, 106095.

Balwinder-Singh, Gaydon, D.S., Humphreys, E., Eberbach, P.L., 2011. The effects of mulch and irrigation management on wheat in Punjab, India—evaluation of the APSIM model. F. Crop. Res. 124, 1–13.

Barlow, K.M., Christy, B.P., O'leary, G.J., Riffkin, P.A., Nuttall, J.G., 2015. Simulating the impact of extreme heat and frost events on wheat crop production: a review. F. Crop. Res. 171, 109–119.

Bell, L.W., Hargreaves, J.N.G., Lawes, R.A., Robertson, M.J., 2009. Sacrificial grazing of wheat crops: identifying tactics and opportunities in Western Australia's grainbelt using simulation approaches. Anim. Prod. Sci. 49, 797–806.

Bell, L.W., Lilley, J.M., Hunt, J.R., Kirkegaard, J.A., 2015. Optimising grain yield and grazing potential of crops across Australia's high-rainfall zone: a simulation analysis. 1. Wheat. Crop Pasture Sci. 66, 332–348.

Bosi, C., Sentelhas, P.C., Huth, N.I., Pezzopane, J.R.M., Andreucci, M.P., Santos, P.M., 2020. APSIM-tropical pasture: a model for simulating perennial tropical grass growth and its parameterisation for palisade grass (*Brachiaria brizantha*). Agric. Syst. 184, 102917.

Brisson, N., Mary, B., Ripoche, D., Jeuffroy, M.H., Ruget, F., Nicoullaud, B., Gate, P., Devienne-Barret, F., Antonioletti, R., Durr, C., et al., 1998. STICS: a generic model for the simulation of crops and their water and nitrogen balances. I. Theory and parameterization applied to wheat and corn.

Brisson, N., Ruget, F., Gate, P., Lorgeou, J., Nicoullaud, B., Tayot, X., Plenet, D., Jeuffroy, M.-H., Bouthier, A., Ripoche, D., et al., 2002. STICS: a generic model for simulating crops and their water and nitrogen balances. II. Model validation for wheat and maize. Agronomie 22, 69–92.

Brisson, N., Gary, C., Justes, E., Roche, R., Mary, B., Ripoche, D., Zimmer, D., Sierra, J., Bertuzzi, P., Burger, P., et al., 2003. An overview of the crop model STICS. Eur. J. Agron. 18, 309–332.

Brown, H.E., Huth, N.I., Holzworth, D.P., Teixeira, E.I., Zyskowski, R.F., Hargreaves, J.N. G., Moot, D.J., 2014. Plant modelling framework: software for building and running crop models on the APSIM platform. Environ. Model. Softw. 62, 385–398.

Brown, H., Huth, N., Holzworth, D., 2018. Crop model improvement in APSIM: using wheat as a case study. Eur. J. Agron. 0–1 https://doi.org/10.1016/j.eja.2018.02.002.

Bryan, B.A., King, D., Zhao, G., 2014. Influence of management and environment on Australian wheat: information for sustainable intensification and closing yield gaps. Environ. Res. Lett. 9, 44005.

Carberry, P.S., Hochman, Z., Hunt, J.R., Dalgliesh, N.P., McCown, R.L., Whish, J.P.M., Robertson, M.J., Foale, M.A., Poulton, P.L., Van Rees, H., 2009. Re-inventing model-based decision support with Australian dryland farmers. 3. Relevance of APSIM to commercial crops. Crop Pasture Sci. 60, 1044–1056.

Carberry, P.S., Liang, W., Twomlow, S., Holzworth, D.P., Dimes, J.P., McClelland, T., Huth, N.I., Chen, F., Hochman, Z., Keating, B.A., 2013. Scope for improved eco-efficiency varies among diverse cropping systems. Proc. Natl. Acad. Sci. 110, 8381–8386.

Casadebaig, P., Zheng, B., Chapman, S., Huth, N., Faivre, R., Chenu, K., 2016. Assessment of the potential impacts of wheat plant traits across environments by combining crop modeling and global sensitivity analysis. PLoS One 11, e0146385.

Chauhan, Y.S., Ryan, M., Chandra, S., Sadras, V.O., 2019. Accounting for soil moisture improves prediction of flowering time in chickpea and wheat. Sci. Rep. 9, 1–11.

Chen, C., Wang, E., Yu, Q., 2010a. Modelling the effects of climate variability and water management on crop water productivity and water balance in the North China Plain. Agric. Water Manag. 97, 1175–1184. https://doi.org/10.1016/j.agwat.2008.11.012.

Chen, C., Wang, E., Yu, Q., 2010b. Modeling wheat and maize productivity as affected by climate variation and irrigation supply in North China Plain. Agron. J. 102, 1037–1049.

Chen, C., Wang, E., Yu, Q., Zhang, Y., 2010c. Quantifying the effects of climate trends in the past 43 years (1961–2003) on crop growth and water demand in the North China Plain. Clim. Chang. 100, 559–578.

Connolly, R.D., Bell, M., Huth, N., Freebairn, D.M., Thomas, G., 2002. Simulating infiltration and the water balance in cropping systems with APSIM-SWIM. Soil Res. 40, 221–242.

Dalgliesh, N.P., Foale, M.A., McCown, R.L., 2009. Re-inventing model-based decision support with Australian dryland farmers. 2. Pragmatic provision of soil information for paddock-specific simulation and farmer decision making. Crop Pasture Sci. 60, 1031–1043.

Dalgliesh, N., Cocks, B., Horan, H., et al., 2012. APSoil-providing soils information to consultants, farmers and researchers. In: 16th Australian Agronomy Conference. Armidale, NSW.

Deihimfard, R., Mahallati, M.N., Koocheki, A., 2015. Yield gap analysis in major wheat growing areas of Khorasan province, Iran, through crop modelling. F. Crop. Res. 184, 28–38.

Deihimfard, R., Eyni-Nargeseh, H., Mokhtassi-Bidgoli, A., 2018. Effect of future climate change on wheat yield and water use efficiency under semi-arid conditions as predicted by APSIM-wheat model. Int. J. Plant Prod. 12, 115–125.

FAO, 2020. World Food and Agriculture - Statistical Yearbook 2020 (Rome).

FAOSTAT Statistical Database, 2017. International Wheat Production Statistics [WWW Document]. Food Agric. Organ. United Nations. URL. http://www.fao.org/faostat/en/#data/QCL/visualize.

Fisher, J.S., Asseng, S., Bowden, J.W., Robertson, M.J., et al., 2001. Trial-years without tears: enhancing recommendations of flowering and yield in wheat. In: Proceedings of the 10th Australian Agronomy Conference, Hobart,(Australian Society of Agronomy). http://www.regional.org.Au/Au/Asa/2001/6/d/Fisher.Htm.

Fletcher, A.L., Chen, C., Ota, N., Lawes, R.A., Oliver, Y.M., 2020. Has historic climate change affected the spatial distribution of water-limited wheat yield across Western Australia? Clim. Chang. 1–18.

Frederiks, T.M., Christopher, J.T., Harvey, G.L., Sutherland, M.W., Borrell, A.K., 2012. Current and emerging screening methods to identify post-head-emergence frost adaptation in wheat and barley. J. Exp. Bot. 63, 5405–5416.

Fuller, M.P., Fuller, A.M., Kaniouras, S., Christophers, J., Fredericks, T., 2007. The freezing characteristics of wheat at ear emergence. Eur. J. Agron. 26, 435–441.

Gaydon, D.S., Lisson, S.N., Xevi, E., et al., 2006. Application of APSIM 'multi-paddock' to estimate whole-of-farm water-use efficiency, system water balance and crop production for a rice-based operation in the Coleambally Irrigation District, NSW. In: Proceedings of the 13th Australian Society of Agronomy Conference, pp. 10–14.

Gaydon, D.S., Wang, E., Poulton, P.L., Ahmad, B., Ahmed, F., Akhter, S., Ali, I., Amarasingha, R., Chaki, A.K., Chen, C., et al., 2017. Evaluation of the APSIM model in cropping systems of Asia. F. Crop. Res. 204, 52–75.

Hammer, G.L., van Oosterom, E., McLean, G., Chapman, S.C., Broad, I., Harland, P., Muchow, R.C., 2010. Adapting APSIM to model the physiology and genetics of complex adaptive traits in field crops. J. Exp. Bot. 61, 2185–2202.

Hansen, J.W., Mishra, A., Rao, K.P.C., Indeje, M., Ngugi, R.K., 2009. Potential value of GCM-based seasonal rainfall forecasts for maize management in semi-arid Kenya. Agric. Syst. 101, 80–90.

He, L., Cleverly, J., Chen, C., Yang, X., Li, J., Liu, W., Yu, Q., 2014. Diverse responses of winter wheat yield and water use to climate change and variability on the semiarid Loess Plateau in China. Agron. J. 106, 1169–1178.

Hochman, Z., Dang, Y.P., Schwenke, G.D., Dalgliesh, N.P., Routley, R., McDonald, M., Daniells, I.G., Manning, W., Poulton, P.L., 2007. Simulating the effects of saline and sodic subsoils on wheat crops growing on Vertosols. Aust. J. Agric. Res. 58, 802–810.

Hochman, Z., Holzworth, D., Hunt, J.R., 2009a. Potential to improve on-farm wheat yield and WUE in Australia. Crop Pasture Sci. 60, 708–716.

Hochman, Z., Van Rees, H., Carberry, P.S., Hunt, J.R., McCown, R.L., Gartmann, A., Holzworth, D., Van Rees, S., Dalgliesh, N.P., Long, W., et al., 2009b. Re-inventing model-based decision support with Australian dryland farmers. 4. Yield Prophet®helps farmers monitor and manage crops in a variable climate. Crop Pasture Sci. 60, 1057–1070.

Hochman, Z., Gobbett, D., Holzworth, D., McClelland, T., van Rees, H., Marinoni, O., Garcia, J.N., Horan, H., 2013. Reprint of "Quantifying yield gaps in rainfed cropping systems: a case study of wheat in Australia". F. Crop. Res. 143, 65–75.

Holzworth, D.P., Huth, N.I., deVoil, P.G., 2011. Simple software processes and tests improve the reliability and usefulness of a model. Environ. Model. Softw. 26, 510–516.

Holzworth, D.P., Huth, N.I., DeVoil, P.G., Zurcher, E.J., Herrmann, N.I., McLean, G., Chenu, K., van Oosterom, E.J., Snow, V., Murphy, C., et al., 2014. APSIM—evolution towards a new generation of agricultural systems simulation. Environ. Model. Softw. 62, 327–350.

Holzworth, D., Huth, N.I., Fainges, J., Brown, H., Zurcher, E., Cichota, R., Verrall, S., Herrmann, N.I., Zheng, B., Snow, V., 2018. APSIM next generation: overcoming challenges in modernising a farming systems model. Environ. Model. Softw. 103, 43–51.

Horie, T., Yajima, M., Nakagawa, H., 1992. Yield forecasting. Agric. Syst. 40, 211–236.

Hsiao, T.C., Heng, L., Steduto, P., Rojas-Lara, B., Raes, D., Fereres, E., 2009. AquaCrop—the FAO crop model to simulate yield response to water: III. Parameterization and testing for maize. Agron. J. 101, 448–459.

Hunt, J., van Rees, H., Hochman, Z., Carberry, P., Holzworth, D., Dalgliesh, N., Brennan, L., Poulton, P., van Rees, S., Huth, N.I., et al., 2006. Yield Prophet®: an online crop simulation service. In: Proceedings of the 13th Australian Agronomy Conference, pp. 10–14.

Hussain, J., Khaliq, T., Ahmad, A., Akhtar, J., 2018. Performance of four crop model for simulations of wheat phenology, leaf growth, biomass and yield across planting dates. PLoS One 13, e0197546.

Iizumi, T., Shin, Y., Kim, W., Kim, M., Choi, J., 2018. Global crop yield forecasting using seasonal climate information from a multi-model ensemble. Clim. Serv. 11, 13–23.

Innes, P.J., Tan, D.K.Y., Van Ogtrop, F., Amthor, J.S., 2015. Effects of high-temperature episodes on wheat yields in New South Wales, Australia. Agric. For. Meteorol. 208, 95–107.

Jones, J.W., Hoogenboom, G., Porter, C.H., Boote, K.J., Batchelor, W.D., Hunt, L.A., Wilkens, P.W., Singh, U., Gijsman, A.J., Ritchie, J.T., 2003. The DSSAT cropping system model. Eur. J. Agron. 18, 235–265.

Jones, C.A., Kiniry, J.R., 1986. CERES-Maize; a Simulation Model of Maize Growth and Development.

Keating, B.S., Meinke, H., Probert, M.E., Huth, N.I., Hills, I.G., et al., 2001. NWheat: Documentation and Performance of a Wheat Module for APSIM.

Keating, B.A., Gaydon, D., Huth, N.I., Probert, M.E., Verburg, K., Smith, C.J., Bond, W., 2002. Use of modelling to explore the water balance of dryland farming systems in the Murray-Darling Basin, Australia. Eur. J. Agron. 18, 159–169.

Keating, B.A., Carberry, P.S., Hammer, G.L., Probert, M.E., Robertson, M.J., Holzworth, D., Huth, N.I., Hargreaves, J.N.G., Meinke, H., Hochman, Z., McLean, G., Verburg, K., Snow, V., Dimes, J.P., Silburn, M., Wang, E., Brown, S., Bristow, K.L., Asseng, S., Chapman, S., McCown, R.L., Freebairn, D.M., Smith, C.J., 2003. An overview of the crop model. Eur. J. Agron. 18, 267–288. https://doi.org/10.1016/S0223-5234(03)00100-4.

Kundzewicz, Z.W., Kanae, S., Seneviratne, S.I., Handmer, J., Nicholls, N., Peduzzi, P., Mechler, R., Bouwer, L.M., Arnell, N., Mach, K., et al., 2014. Flood risk and climate change: global and regional perspectives. Hydrol. Sci. J. 59, 1–28.

Lawes, R.A., Oliver, Y.M., Robertson, M.J., 2009. Integrating the effects of climate and plant available soil water holding capacity on wheat yield. F. Crop. Res. 113, 297–305.

Li, K., Yang, X., Liu, Z., Zhang, T., Lu, S., Liu, Y., 2014. Low yield gap of winter wheat in the North China Plain. Eur. J. Agron. 59, 1–12.

Li, J., Wang, E., Wang, Y., Xing, H., Wang, D., Wang, L., Gao, C., 2016. Reducing greenhouse gas emissions from a wheat–maize rotation system while still maintaining productivity. Agric. Syst. 145, 90–98.

Lilley, J.M., Kirkegaard, J.A., 2008. Seasonal variation in the value of subsoil water to wheat: simulation studies in southern New South Wales. Aust. J. Agric. Res. 58, 1115–1128.

Lilley, J.M., Kirkegaard, J.A., Robertson, M.J., Probert, M.E., Angus, J.F., Howe, G., 2003. Simulating crop and soil processes in crop sequences in southern NSW. In: Proceedings of the 11th Australian Agronomy Conference'. Geelong.

Littleboy, M., Silburn, D.M., Freebairn, D.M., Woodruff, D.R., Hammer, G.L., Leslie, J.K., 1992. Impact of soil erosion on production in cropping systems. I. Development and validation of a simulation model. Soil Res. 30, 757–774.

Liu, B., Asseng, S., Liu, L., Tang, L., Cao, W., Zhu, Y., 2016a. Testing the responses of four wheat crop models to heat stress at anthesis and grain filling. Glob. Chang. Biol. 22, 1890–1903.

Liu, B., Asseng, S., Müller, C., Ewert, F., Elliott, J., Lobell, D.B., Martre, P., Ruane, A.C., Wallach, D., Jones, J.W., Rosenzweig, C., Aggarwal, P.K., Alderman, P.D., Anothai, J., Basso, B., Biernath, C., Cammarano, D., Challinor, A., Deryng, D., De Sanctis, G., Doltra, J., Fereres, E., Folberth, C., Garcia-Vila, M., Gayler, S., Hoogenboom, G., Hunt, L.A., Izaurralde, R.C., Jabloun, M., Jones, C.D., Kersebaum, K.C., Kimball, B.A., Koehler, A.K., Kumar, S.N., Nendel, C., O'Leary, G. J., Olesen, J.E., Ottman, M.J., Palosuo, T., Prasad, P.V.V., Priesack, E., Pugh, T.A.M., Reynolds, M., Rezaei, E.E., Rötter, R.P., Schmid, E., Semenov, M.A., Shcherbak, I., Stehfest, E., Stöckle, C.O., Stratonovitch, P., Streck, T., Supit, I., Tao, F., Thorburn, P., Waha, K., Wall, G.W., Wang, E., White, J.W., Wolf, J., Zhao, Z., Zhu, Y., 2016b. Similar estimates of temperature impacts on global wheat yield by three independent methods. Nat. Clim. Chang. 6, 1130–1136. https://doi.org/10.1038/nclimate3115.

Lobell, D.B., Sibley, A., Ivan Ortiz-Monasterio, J., 2012. Extreme heat effects on wheat senescence in India. Nat. Clim. Chang. 2, 186–189. https://doi.org/10.1038/nclimate1356.

Luck, J., Spackman, M., Freeman, A., Tre¸bicki, P., Griffiths, W., Finlay, K., Chakraborty, S., 2011. Climate change and diseases of food crops. Plant Pathol. 60, 113–121.

Ludwig, F., Asseng, S., 2006. Climate change impacts on wheat production in a Mediterranean environment in Western Australia. Agric. Syst. 90, 159–179.

Luo, Q., Bellotti, W., Williams, M., Bryan, B., 2005. Potential impact of climate change on wheat yield in South Australia. Agric. For. Meteorol. 132, 273–285.

Maiorano, A., Martre, P., Asseng, S., Ewert, F., Müller, C., Rötter, R.P., Ruane, A.C., Semenov, M.A., Wallach, D., Wang, E., Alderman, P.D., Kassie, B.T., Biernath, C., Basso, B., Cammarano, D., Challinor, A.J., Doltra, J., Dumont, B., Rezaei, E.E., Gayler, S., Kersebaum, K.C., Kimball, B.A., Koehler, A.K., Liu, B., O'Leary, G.J., Olesen, J.E., Ottman, M.J., Priesack, E., Reynolds, M., Stratonovitch, P., Streck, T., Thorburn, P.J., Waha, K., Wall, G.W., White, J.W., Zhao, Z., Zhu, Y., 2017. Crop model improvement reduces the uncertainty of the response to temperature of multi-model ensembles. F. Crop. Res. 202, 5–20. https://doi.org/10.1016/j.fcr.2016.05.001.

Manschadi, A.M., Christopher, J., deVoil, P., Hammer, G.L., 2006. The role of root architectural traits in adaptation of wheat to water-limited environments. Funct. Plant Biol. 33, 823–837.

Martre, P., Quilot-Turion, B., Luquet, D., Memmah, M.-M.O.-S., Chenu, K., Debaeke, P., 2015a. Model-assisted phenotyping and ideotype design. In: Crop Physiology. Elsevier, pp. 349–373.

Martre, P., Wallach, D., Asseng, S., Ewert, F., Jones, J.W., Rötter, R.P., Boote, K.J., Ruane, A.C., Thorburn, P.J., Cammarano, D., et al., 2015b. Multimodel ensembles of wheat growth: many models are better than one. Glob. Chang. Biol. 21, 911–925.

McCown, R.L., Hammer, G.L., Hargreaves, J.N.G., Holzworth, D., Huth, N.I., 1995. APSIM: an agricultural production system simulation model for operational research. Math. Comput. Simul. 39, 225–231. https://doi.org/10.1016/0378-4754(95)00063-2.

McCown, R.L., Hammer, G.L., Hargreaves, J.N.G., Holzworth, D.P., Freebairn, D.M., 1996. APSIM- a novel software system for model development.pdf. Agric. Syst. 50, 255–271.

Meehl, G.A., Zwiers, F., Evans, J., Knutson, T., Mearns, L., Whetton, P., 2000. Trends in extreme weather and climate events: issues related to modeling extremes in projections of future climate change. Bull. Am. Meteorol. Soc. 81, 427–436.

Mielenz, H., Thorburn, P.J., Scheer, C., Migliorati, M.D.A., Grace, P.R., Bell, M.J., 2016. Opportunities for mitigating nitrous oxide emissions in subtropical cereal and fiber cropping systems: a simulation study. Agric. Ecosyst. Environ. 218, 11–27.

Moeller, C., Pala, M., Manschadi, A.M., Meinke, H., Sauerborn, J., 2007. Assessing the sustainability of wheat-based cropping systems using APSIM: model parameterisation and evaluation. Aust. J. Agric. Res. 58, 75–86.

Mohanty, M., Probert, M.E., Reddy, K.S., Dalal, R.C., Mishra, A.K., Subba Rao, A., Singh, M., Menzies, N.W., 2012. Simulating soybean-wheat cropping system: APSIM model parameterization and validation. Agric. Ecosyst. Environ. 152, 68–78. https://doi.org/10.1016/j.agee.2012.02.013.

Neitsch, S.L., Arnold, J.G., Kiniry, J.R., Williams, J.R., 2011. Soil and Water Assessment Tool Theoretical Documentation Version 2009.

O'Leary, G.J., Christy, B., Nuttall, J., Huth, N., Cammarano, D., Stöckle, C., Basso, B., Shcherbak, I., Fitzgerald, G., Luo, Q., et al., 2015. Response of wheat growth, grain yield and water use to elevated CO 2 under a Free-Air CO 2 Enrichment (FACE) experiment and modelling in a semi-arid environment. Glob. Chang. Biol. 21, 2670–2686.

O'Leary, G.J., Li Liu, D., Ma, Y., Li, F.Y., McCaskill, M., Conyers, M., Dalal, R., Reeves, S., Page, K., Dang, Y.P., et al., 2016. Modelling soil organic carbon 1. Performance of APSIM crop and pasture modules against long-term experimental data. Geoderma 264, 227–237.

Oliver, Y.M., Robertson, M.J., 2009. Quantifying the benefits of accounting for yield potential in spatially and seasonally responsive nutrient management in a Mediterranean climate. Soil Res. 47, 114–126.

Oliver, Y., Wong, M., Robertson, M., Wittwer, K., et al., 2006. PAWC determines spatial variability in grain yield and nitrogen requirement by interacting with rainfall on northern WA sandplain. In: Proceedings of the 13th Australian Agronomy Conference, pp. 10–14.

Oliver, Y.M., Robertson, M.J., Stone, P.J., Whitbread, A., 2009. Improving estimates of water-limited yield of wheat by accounting for soil type and within-season rainfall. Crop Pasture Sci. 60, 1137–1146.

Paydar, Z., Huth, N., Ringrose-Voase, A., Young, R., Bernardi, T., Keating, B., Cresswell, H., 2005. Deep drainage and land use systems. Model verification and systems comparison. Aust. J. Agric. Res. 56, 995–1007.

Peake, A.S., Huth, N.I., Carberry, P.S., Raine, S.R., Smith, R.J., 2014. Quantifying potential yield and lodging-related yield gaps for irrigated spring wheat in sub-tropical Australia. F. Crop. Res. 158, 1–14.

Peel, M.C., Finlayson, B.L., McMahon, T.A., 2007. Updated world map of the Köppen-Geiger climate classification. Hydrol. Earth Syst. Sci. 11, 1633–1644.

Perkins, S.E., Alexander, L.V., Nairn, J.R., 2012. Increasing frequency, intensity and duration of observed global heatwaves and warm spells. Geophys. Res. Lett. 39.

Phelan, D.C., Harrison, M.T., McLean, G., Cox, H., Pembleton, K.G., Dean, G.J., Parsons, D., do Amaral Richter, M.E., Pengilley, G., Hinton, S.J., et al., 2018. Advancing a farmer decision support tool for agronomic decisions on rainfed and irrigated wheat cropping in Tasmania. Agric. Syst. 167, 113–124.

Probert, M.E., Dimes, J.P., 2004. Modelling release of nutrients from organic resources using APSIM. In: ACIAR Proceedings, pp. 25–31.

Probert, M.E., Keating, B.A., Thompson, J.P., Parton, W.J., 1995. Modelling water, nitrogen, and crop yield for a long-term fallow management experiment. Aust. J. Exp. Agric. 35, 941–950.

Probert, M.E., Carberry, P.S., McCown, R.L., Turpin, J.E., 1998. Simulation of legume-cereal systems using APSIM. Aust. J. Agric. Res. 49, 317–328.

Raes, D., Steduto, P., Hsiao, T.C., Fereres, E., 2009. AquaCrop—the FAO crop model to simulate yield response to water: II. Main algorithms and software description. Agron. J. 101, 438–447.

Rigby, J.R., Porporato, A., 2008. Spring frost risk in a changing climate. Geophys. Res. Lett. 35.

Roberts, M.J., Braun, N.O., Sinclair, T.R., Lobell, D.B., Schlenker, W., 2017. Comparing and combining process-based crop models and statistical models with some implications for climate change. Environ. Res. Lett. 12, 95010.

Robertson, M.J., Lilley, J.M., 2016. Simulation of growth, development and yield of canola (*Brassica napus*) in APSIM. Crop Pasture Sci. 67, 332–344.

Robertson, M.J., Carberry, P.S., Huth, N.I., Turpin, J.E., Probert, M.E., Poulton, P.L., Bell, M., Wright, G.C., Yeates, S.J., Brinsmead, R.B., 2002. Simulation of growth and development of diverse legume species in APSIM. Aust. J. Agric. Res. 53, 429–446.

Rötter, R.P., Tao, F., Höhn, J.G., Palosuo, T., 2015. Use of crop simulation modelling to aid ideotype design of future cereal cultivars. J. Exp. Bot. 66, 3463–3476.

Sadras, V., Baldock, J., Roget, D., Rodriguez, D., 2003. Measuring and modelling yield and water budget components of wheat crops in coarse-textured soils with chemical constraints. F. Crop. Res. 84, 241–260.

Shamudzarira, Z., Robertson, M.J., 2002. Simulating response of maize to nitrogen fertilizer in semi-arid Zimbabwe. Exp. Agric. 38, 79–96.

Shiferaw, B., Smale, M., Braun, H.-J., Duveiller, E., Reynolds, M., Muricho, G., 2013. Crops that feed the world 10. Past successes and future challenges to the role played by wheat in global food security. Food Secur. 5, 291–317.

Shroyer, J.P., Mikesell, M.E., Paulsen, G.M., 1995. Spring freeze injury to Kansas wheat. In: Cooperative Extension Service. Kansas State University.

Soltani, A., Sinclair, T.R., 2015. A comparison of four wheat models with respect to robustness and transparency: simulation in a temperate, sub-humid environment. F. Crop. Res. 175, 37–46.

Steduto, P., Hsiao, T.C., Raes, D., Fereres, E., 2009. AquaCrop—the FAO crop model to simulate yield response to water: I. Concepts and underlying principles. Agron. J. 101, 426–437.

Stone, P.J., Nicolas, M.E., 1995. A survey of the effects of high temperature during grain filling on yield and quality of 75 wheat cultivars. Aust. J. Agric. Res. 46, 475–492.

Sun, H., Zhang, X., Wang, E., Chen, S., Shao, L., 2015. Quantifying the impact of irrigation on groundwater reserve and crop production—a case study in the North China Plain. Eur. J. Agron. 70, 48–56.

Tao, F., Rötter, R.P., Palosuo, T., Díaz-Ambrona, Carlos Gregorio Hernández, Mínguez, M. Inés, Semenov, M.A., Kersebaum, K.C., Nendel, C., Specka, X., Hoffmann, H., et al., 2018. Contribution of crop model structure, parameters and climate projections to uncertainty in climate change impact assessments. Glob. Chang. Biol. 24, 1291–1307.

Thorburn, P.J., Probert, M.E., Robertson, F.A., 2001. Modelling decomposition of sugar cane surface residues with APSIM—residue. F. Crop. Res. 70, 223–232.

Trenberth, K.E., 2011. Changes in precipitation with climate change. Clim. Res. 47, 123–138.

Van Dam, J.C., Huygen, J., Wesseling, J.G., Feddes, R.A., Kabat, P., Van Walsum, P.E., Groenendijk, P., Van Diepen, C.A., 1997. Theory of SWAP Version 2.0 Simulation of Water Flow, Solute Transport and Plant Growth in the Soil-Water-Atmosphere-Plant Environment.

Van Diepen, C.A., Wolf, J., Van Keulen, H., Rappoldt, C., 1989. WOFOST: a simulation model of crop production. Soil Use Manag. 5, 16–24.

van Ittersum, M.K., Leffelaar, P.A., Van Keulen, H., Kropff, M.J., Bastiaans, L., Goudriaan, J., 2003. On approaches and applications of the Wageningen crop models. Eur. J. Agron. 18, 201–234.

Van Oort, P.A.J., Wang, G., Vos, J., Meinke, H., Li, B.G., Huang, J.K., van der Werf, W., 2016. Towards groundwater neutral cropping systems in the Alluvial Fans of the North China Plain. Agric. Water Manag. 165, 131–140.

Van Wijk, M.T., Rufino, M.C., Enahoro, D., Parsons, D., Silvestri, S., Valdivia, R.O., Herrero, M., 2014. Farm household models to analyse food security in a changing climate: a review. Glob. Food Sec. 3, 77–84.

Vrugt, J.A., Ter Braak, C.J.F., Clark, M.P., Hyman, J.M., Robinson, B.A., 2008. Treatment of input uncertainty in hydrologic modeling: doing hydrology backward with Markov chain Monte Carlo simulation. Water Resour. Res. 44.

Wang, E., Van Oosterom, E., Meinke, H., Asseng, S., Robertson, M.J., Huth, N., Keating, B., Probert, M., 2003. The new APSIM-Wheat Model—performance and future improvements. In: Proceedings of the 11th Australian Agronomy Conference.

Wang, E., Chen, C., Yu, Q., 2009. Modeling the response of wheat and maize productivity to climate variability and irrigation in the North China Plain. In: 18th World IMACS/MODSIM Congress, pp. 2742–2748.

Wang, J., Wang, E., Feng, L., Yin, H., Yu, W., 2013. Phenological trends of winter wheat in response to varietal and temperature changes in the North China Plain. F. Crop. Res. 144, 135–144.

Wang, G.-C., Wang, E.-L., Yao, H., Xu, J.-J., 2014. Soil carbon sequestration potential as affected by management practices in northern China: a simulation study. Pedosphere 24, 529–543.

Wang, E., Martre, P., Zhao, Z., Ewert, F., Maiorano, A., Rötter, R.P., Kimball, B.A., Ottman, M.J., Wall, G.W., White, J.W., et al., 2017. The uncertainty of crop yield projections is reduced by improved temperature response functions. Nat. Plants 3, 17102.

Williams, J.R., Jones, C.A., Kiniry, J.R., Spanel, D.A., 1989. The EPIC crop growth model. Trans. ASAE 32, 497–511.

Wong, M.T.F., Asseng, S., 2006. Determining the causes of spatial and temporal variability of wheat yields at sub-field scale using a new method of upscaling a crop model. Plant Soil 283, 203–215.

Xiao, D., Tao, F., 2014. Contributions of cultivars, management and climate change to winter wheat yield in the North China Plain in the past three decades. Eur. J. Agron. 52, 112–122.

Yan, Z., Zhang, X., Rashid, M.A., Li, H., Jing, H., Hochman, Z., 2020. Assessment of the sustainability of different cropping systems under three irrigation strategies in the North China Plain under climate change. Agric. Syst. 178, 102745.

Yang, Yanmin, Li Liu, D., Anwar, M.R., Zuo, H., Yang, Yonghui, 2014. Impact of future climate change on wheat production in relation to plant-available water capacity in a semiaridenvironment. Theor. Appl. Climatol. 115, 391–410.

Yunusa, I.A.M., Bellotti, W.D., Moore, A.D., Probert, M.E., Baldock, J.A., Miyan, S.M., 2004. An exploratory evaluation of APSIM to simulate growth and yield processes for winter cereals in rotation systems in South Australia. Aust. J. Exp. Agric. 44, 787–800.

Zadoks, J.C., Chang, T.T., Konzak, C.F., 1974. A decimal code for the growth stages of cereals. Weed Res. 14, 415–421.

Zeleke, K.T., Nendel, C., 2016. Analysis of options for increasing wheat (*Triticum aestivum* L.) yield in south-eastern Australia: the role of irrigation, cultivar choice and time of sowing. Agric. Water Manag. 166, 139–148.

Zeppel, M.J.B., Wilks, J.V., Lewis, J.D., 2014. Impacts of extreme precipitation and seasonal changes in precipitation on plants. Biogeosciences 11, 3083–3093.

Zhang, Y., Feng, L., Wang, E., Wang, J., Li, B., 2012. Evaluation of the APSIM-Wheat model in terms of different cultivars, management regimes and environmental conditions. Can. J. Plant Sci. 92, 937–949.

Zhang, Y., Feng, L.P., Wang, J., Wang, E.L., Xu, Y.L., 2013. Using APSIM to explore wheat yield response to climate change in the North China Plain: the predicted adaptation of wheat cultivar types to vernalization. J. Agric. Sci. 151, 836–848.

Zhao, Z., Wang, E., Wang, Z., Zang, H., Liu, Y., Angus, J.F., 2014a. A reappraisal of the critical nitrogen concentration of wheat and its implications on crop modeling. F. Crop. Res. 164, 65–73.

Zhao, Z., Wang, E., Xue, L., Wu, Y., Zang, H., Qin, X., Zhang, J., Wang, Z., 2014b. Accuracy of root modelling and its impact on simulated wheat yield and carbon cycling in soil. F. Crop. Res. 165, 99–110.

Zhao, Z., Qin, X., Wang, E., Carberry, P., Zhang, Y., Zhou, S., Zhang, X., Hu, C., Wang, Z., 2015. Modelling to increase the eco-efficiency of a wheat—maize double cropping system. Agric. Ecosyst. Environ. 210, 36–46.

Zhao, J., Pu, F., Li, Y., Xu, J., Li, N., Zhang, Y., Guo, J., Pan, Z., 2017. Assessing the combined effects of climatic factors on spring wheat phenophase and grain yield in Inner Mongolia, China. PLoS One 12.

Zheng, B., Chapman, S.C., Christopher, J.T., Frederiks, T.M., Chenu, K., 2015. Frost trends and their estimated impact on yield in the Australian wheatbelt. J. Exp. Bot. 66, 3611–3623.

Zheng, B., Chenu, K., Doherty, A., Chapman, S., 2014. The APSIM-wheat module (7.5 R3008). Agric. Prod. Syst. Simulator Initiat. 615, 1–42.

Zhou, S., Zhang, Y., Williams, A.P., Gentine, P., 2019. Projected increases in intensity, frequency, and terrestrial carbon costs of compound drought and aridity events. Sci. Adv. 5, eaau5740.