Received: 24 September 2023 | Accepted: 23 February 2024 | Published online: 21 April 2024

DOI: 10.1002/agj2.21567

Agronomy Journal

ORIGINAL ARTICLE

Biometry, Modeling, and Statistics

# Validating APSIM for the Northern Territory of Australia: An environment with challenging weather and soils

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Assigned to Associate Editor Nilovna Chatterjee.

**Funding information**
Cooperative Research Centre for Developing Northern Australia

**Abstract**

Extreme weather (high rainfall and temperatures) and challenging soils are sources of uncertainties in the use of current crop models that have been developed for more favorable environments. This may limit their applicability to guide and support decision making for the development of new agricultural regions in tropical environments. We evaluated the accuracy of the Agricultural Production Systems Simulator (APSIM) framework in representing yield and development of a range of crops across multiple locations in the Northern Territory of Australia, a tropical region with large potential for agricultural development. Observations of yield, biomass, and phenology for a range of crops from 28 experiments undertaken at three locations were compiled and used to develop simulations undertaken using APSIM version 7.10. Model performance varied with coefficients of determination and concordance correlation coefficients ranging from 0.36 to 0.98 and 0.37 to 0.93, respectively. Instances where model performance was less than ideal were associated with conditions presenting a limited number of observed values. Deviations by the model from yield observations were larger for situations with high-yielding crops and low daily maximum temperatures during vegetative growth stages. Deviations in phenology were larger for conditions associated with water and N stress. APSIM was capable of representing the yield, biomass, and development of cereal and pulse crops and can be used with confidence to assist the expansion of agriculture in tropical environments such as the Northern Territory of Australia.

## 1 | INTRODUCTION

Agricultural development and intensification provide local and regional economic benefits while driving an increase in the global food supply. A region currently undergoing agricultural development and intensification on a wide scale is the Northern Territory of Australia. This region has long been suggested as a new field crop region (Ash et al., 2017; Chapman et al., 1996) to complement its well-established extensive grazing sector. Multiple attempts have been made to establish a field cropping industry in the region with limited success to date (Cook, 2009). The Northern Territory has significant water resources and soils suitable for cropping that make the region attractive for agricultural development (CSIRO, 2009; Northern Australia Land and Water Taskforce, 2009; Wilson et al., 2009). Furthermore, opportunities to develop both local and export-based markets and processing are driving renewed

**Abbreviations:** APSIM, Agricultural Production Systems Simulator; CCC, concordance correlation coefficient; RMSE, residual mean square error.

interest in its agricultural development (Ash et al., 2017). To facilitate a transition from pastoral-based agriculture to large-scale cropping that minimizes the risks for producers and their financiers and avoids the failures of the past will require the rapid development of experience and understanding of crop growth and performance in locations where this experience is limited to a few years of experimental work (Ash et al., 2017).

Cropping systems modeling has a key role to play in guiding this development; however, before a crop model can be applied with confidence, it should be evaluated for the environmental conditions it is to be used under. This is to ensure it appropriately represents crop growth in these conditions (Bellocchi et al., 2010). Tropical environments can present some unique challenges to crop models (Rötter et al., 2018), such as extremes in temperatures during key growth stages, challenging soils, and extreme rainfall events (and associated nitrogen [N] leaching).

Cropping systems modeling and their derivative decision support tools have a key role in extending the limited field research by analyzing scenarios over long time periods to develop a full picture of crop performance and potential risks and challenges (McCown, 2002; Whitebread et al., 2010). Major cropping system models have a primary development and testing history focused on temperate and subtropical environments. The Agricultural Production Systems Simulator (APSIM) (D. P. Holzworth et al., 2014) is a farming systems model used worldwide to examine broad-acre, mixed, and smallholder farming systems. It provides the analytical core of several decision support tools (e.g., Hochman et al., 2009; Phelan et al., 2018) that enable farmers to develop their understanding of crop growth and forecast crop yield in response to growing conditions. It has been shown to effectively represent crop growth and development across a broad range of environments and production systems (Kisaka et al., 2016; Pembleton et al., 2013; Shukr et al., 2021), under a range of different cropping inputs and systems (Kisaka et al., 2016; Gaydon et al., 2021; Probert et al., 1998) and climate scenarios (Morel et al., 2021; Pembleton et al., 2016, 2020). Evaluation of the model in tropical environments, while promising, has to date been primarily limited to rice (*Oryza sativa* L.), cotton (*Gossypium hirsutum* L.), and sugar cane (*Saccharum officinarum* L.) crops under specific production conditions (Gaydon et al., 2017; Meier & Thorburn, 2016; Radanielson et al., 2018; Rhebergen & Yeates, 2023).

Early versions of the APSIM model were evaluated for one location in the Northern Territory (Carberry et al., 1996). However, there has been considerable development of the framework since this evaluation (described in Keating et al. [2003] and D. P. Holzworth et al. [2014]), and this model is being applied to guide government policy and industry development (CSIRO, 2018). Therefore, a new evaluation is required so the APSIM framework can be used with confidence and to identify areas that require further development effort. Effort has begun on this for cotton (Rhebergen & Yeates, 2023) but so far, no evaluation has been undertaken for the other crops of interest.

**Core Ideas**

- The accuracy of crop models for environments frequented by challenging weather and soils is rarely reported.
- We showed that the Agricultural Production Systems Simulator (APSIM) performs well in one such environment, the Northern Territory of Australia.
- APSIM can be used with confidence in environments with challenging weather and soil conditions.

The study reported here describes an evaluation of the APSIM model for its ability to represent crop growth and yield in the Northern Territory of Australia. Specifically, it evaluates the models' accuracy in representing the yield and growth of the field crops maize (*Zea mays* L.), sorghum [*Sorghum bicolor* (L.) Moench], rice (*Oryza sativa* L.), soybean [*Glycine max* (L.) Merr.], and mungbean [*Vigna radiate* (L.) R. Wilczek]. These crops have been identified due to local interest and supply into feedlots, potential to develop and supply export markets into Asia, suitability for the climate, and fit within a crop rotation with cotton. This study also investigates if extreme weather events and soil resources supply influence the accuracy of APSIM to identify priorities for future development.

## 2 | MATERIALS AND METHODS

### 2.1 | Crop growth, phenology, and yield data collation

Data relating to the yield, growth, and phenology of maize, sorghum, rice, soybean, and mungbean were collated from three locations in the Northern Territory (Figure 1). These datasets were identified through internet searchers (using www.google.com.au and www.scholar.google.com.au/) with the search terms of the crops name and Northern Territory between October and November 2020. Before a dataset was included, it was confirmed that limitations that the APSIM framework cannot represent (pests, diseases, and nutrient limitations other than N) were not reported as impacting crop growth. The data consisted of a mixture of experiments reported in peer-reviewed publications, reports to industry, and research project reports. The datasets included replicated

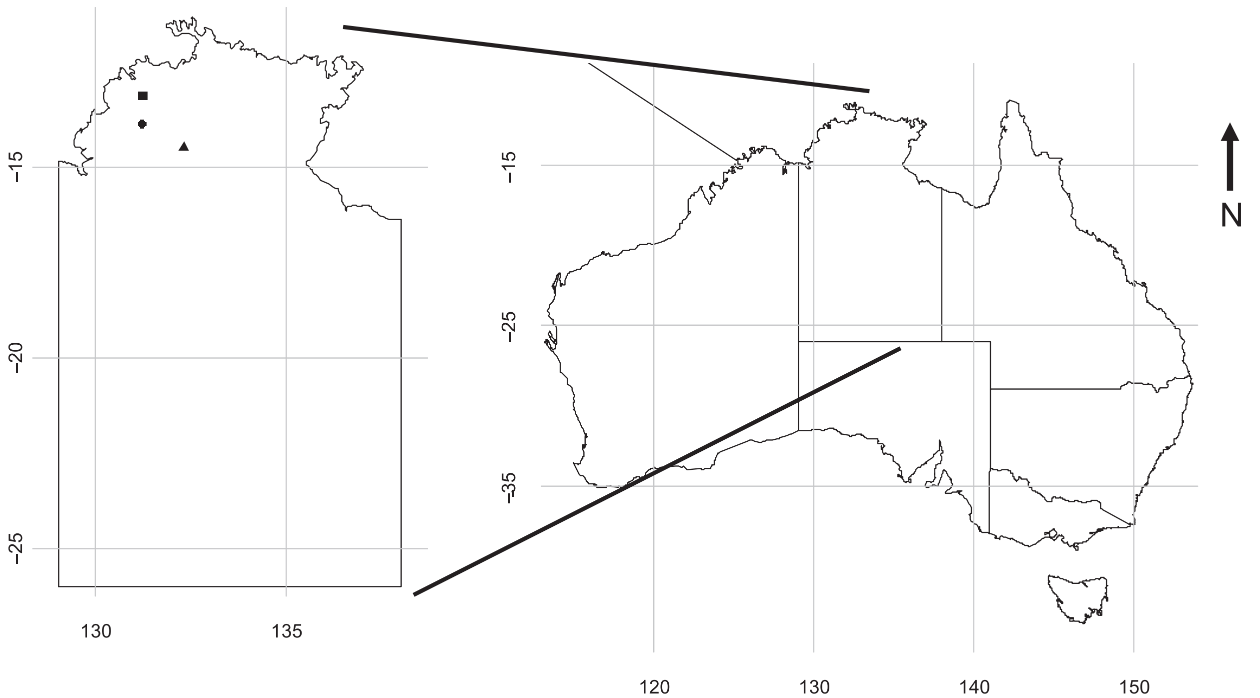


**FIGURE 1** Map of the Northern Territory, Australia, with collection locations from which the validation data was sourced from (●: Douglas Daly, ▲: Katherine, ■: Tortilla Flats).

experiments and unreplicated demonstration crops. Data were extracted directly from tables and by manually digitizing figures. If data were part of a time series, all data points in the time series were extracted. All crops other than soybeans were represented over at least two different locations and in at least two different datasets. A summary of the data is provided in Table 1 with further details provided in Table S1.

## 2.2 | Simulation of crops

Maize, sorghum, rice, soybean, and mungbean crops were simulated with corresponding crop modules within APSIM version 7.10. No modifications were made to each crop representation in the model. Metrological inputs for the simulations were sourced from the Scientific Information for Land Owners database (www.longpaddock.qld.gov.au/silo) as patched point datasets (Jeffrey et al., 2001) of observations at each location. A summary of this data is presented in Table 2. Soil profile descriptions for each location (Table 3) information was sourced from literature and the comprehensive description of agricultural soils in the region reported by Hill et al. (2011). Soil conditions were initialized based on information provided with the datasets or where information was not available, running the simulation as a fallow from the previous crop as reported with the dataset. Management operations (cultivation, fertilizer inputs, and irrigation practices) were informed from what was reported with the datasets. Crop cultivar characteristics were input from the model crop specific parameters library for existing cultivars parameterized in APSIM, and for varieties not in APSIM, we selected the existing cultivar with the closest matching characteristics particularly in terms of maturity type. Model outputs evaluated were crop yield, biomass, the days after sowing for flowering and maturity growth stages, and stress factors (a range from 0 to 1, where 0 is fully stressed and 1 is no stress). For all crops, the water stress factor on leaf expansion was output (*lestrs*, *swdef_expan*, *swdef_expan*, *sw_stress_expan*, and *sw_stress_expan* for rice, maize, sorghum, soybean, and mungbean, respectively). For N stress in rice, the N stress factor on leaf growth (*rnstrs*) was output, while for the other crops, the N stress factor on photosynthesis (*nfact_photo*, *nfact_photo*, *n_stress_photo*, and *n_stress_photo* for maize, sorghum, soybean, and mungbean, respectively) was output.

## 2.3 | Evaluation of model performance

Modeled and observed data were compared as scatter plots with the observed values on the *y* axis and the modeled values on the *x* axis (Piñeiro et al., 2008). Furthermore, to highlight the magnitude of differences between average measured and modeled data for all crops and locations, a Bland–Altman plot was drawn (Martin Bland & Altman, 1986). These plot

**TABLE 1** Summary of crop datasets from the Northern Territory, Australia, used for the validation of the Agricultural Production Systems Simulator (APSIM).

| Crop | Location | Sowing dates | Fertilizer | Irrigation practices | No. of yield observations | No. of biomass observations | No. of growth stage observations | References |
|---|---|---|---|---|---|---|---|---|
| Rice | Katherine | Mid May | 150.6 kg N/ha | Fully irrigated | 10 | 10 | 10 | Eastick et al. (2012) |
| | Tortilla Flats | Mid Dec. to late May | 127.6 and 150.6 kg N/ha | Ponded | 43 | 34 | 32 | Eastick et al. (2012), Sivapalan (2016) |
| Soybean | Douglas Daly | Early Dec. to late Feb. | 0–130 kg N/ha | Dryland and irrigated | 45 | 12 | 28 | Garside and Buchanan (n.d.), Thiagalingam et al. (1996) |
| Maize | Douglas Daly | Early Dec. to late April | 180–330 kg N/ha | Irrigated | 56 | 0 | 0 | O'Gara (2007), Thiagalingam et al. (1996) |
| | Katherine | Early Dec. and mid Jan. | 105 kg N/ha | Irrigated and dryland | 4 | 0 | 0 | Jones et al. (1996), Muchow (1989) |
| Grain sorghum | Douglas Daly | Mid Nov. and mid Dec. | 80 kg N/ha | Dryland and irrigated | 20 | 0 | 0 | Shotton (2000), Thiagalingam et al. (1996) |
| | Katherine | Early Dec. to mid Jan. | 0–150 kg N/ha | Irrigated | 3 | 0 | 0 | Dimes et al. (1996), Muchow (1990), Muchow (1989) |
| Mungbean | Douglas Daly | Mid Dec. | None | Dryland | 2 | 0 | 0 | Thiagalingam et al. (1996) |
| | Katherine | Mid Dec. | None | Irrigated | 3 | 0 | 0 | Yeates and Imrie (1993) |

**TABLE 2** Long-term (1901–2022) monthly maximum and minimum temperature and monthly rainfall for each of the study locations of Katherine, Tortilla Flats, and Douglas Daly, Northern Territory. Data sourced from Scientific Information for Land Owners (www.longpaddock.qld.gov.au/silo/; Jeffrey et al., 2001).

| | Katherine | | | Tortilla Flats | | | Douglas Daly | | |
|---|---|---|---|---|---|---|---|---|---|
| Month | Maximum temperature (˚C) | Minimum temperature (˚C) | Rainfall (mm) | Maximum temperature (˚C) | Minimum temperature (˚C) | Rainfall (mm) | Maximum temperature (˚C) | Minimum temperature (˚C) | Rainfall (mm) |
| January | 34.8 | 24.2 | 235 | 33.2 | 24.1 | 308 | 33.8 | 24.0 | 267 |
| February | 34.2 | 23.9 | 223 | 32.9 | 23.9 | 284 | 33.4 | 23.8 | 264 |
| March | 34.4 | 23.2 | 157 | 33.3 | 23.7 | 238 | 33.9 | 23.3 | 205 |
| April | 34.3 | 20.7 | 34 | 33.9 | 21.9 | 70 | 34.4 | 20.8 | 44 |
| May | 32.3 | 17.4 | 5 | 32.9 | 19.1 | 9 | 33.0 | 17.6 | 6 |
| June | 30.3 | 14.4 | 2 | 31.5 | 16.6 | 2 | 31.1 | 14.6 | 2 |
| July | 30.3 | 13.3 | 2 | 31.7 | 15.8 | 1 | 31.4 | 13.7 | 2 |
| August | 32.5 | 15.0 | 0 | 33.3 | 16.8 | 1 | 33.3 | 15.1 | 1 |
| September | 35.7 | 19.7 | 6 | 35.7 | 20.2 | 11 | 36.2 | 19.2 | 6 |
| October | 37.7 | 23.6 | 27 | 36.7 | 23.1 | 50 | 37.4 | 22.7 | 40 |
| November | 37.8 | 24.8 | 88 | 36.0 | 24.1 | 129 | 36.8 | 23.8 | 118 |
| December | 36.2 | 24.6 | 191 | 34.5 | 24.3 | 223 | 35.1 | 24.1 | 207 |
| Annual average/total | 34.2 | 20.6 | 970 | 33.8 | 21.1 | 1326 | 34.2 | 20.2 | 1162 |

TABLE 3 Soil properties used for the simulation of the crops at Katherine, Tortilla Flats, and Douglas Daly, Northern Territory.

| Depth (cm) | Bulk density ($g/cm^3$) | Air dry water content (mm/mm) | Lower limit (mm/mm) | Drained upper limit (mm/mm) | Saturated water content (mm/mm) |
|---|---|---|---|---|---|
| **Katherine** | | | | | |
| 0–15 | 1.402 | 0.066 | 0.131 | 0.251 | 0.441 |
| 15–30 | 1.460 | 0.099 | 0.124 | 0.250 | 0.419 |
| 30–60 | 1.577 | 0.099 | 0.099 | 0.259 | 0.375 |
| 60–90 | 1.504 | 0.119 | 0.119 | 0.240 | 0.402 |
| 90–120 | 1.549 | 0.119 | 0.119 | 0.262 | 0.386 |
| 120–150 | 1.604 | 0.119 | 0.119 | 0.268 | 0.365 |
| 150–180 | 1.514 | 0.119 | 0.119 | 0.265 | 0.399 |
| 180–300 | 1.514 | 0.119 | 0.119 | 0.265 | 0.399 |
| **Tortilla Flats** | | | | | |
| 0–15 | 1.473 | 0.044 | 0.133 | 0.240 | 0.385 |
| 15–30 | 1.530 | 0.050 | 0.149 | 0.249 | 0.373 |
| 30–45 | 1.548 | 0.058 | 0.175 | 0.273 | 0.374 |
| 45–60 | 1.555 | 0.064 | 0.193 | 0.291 | 0.376 |
| 60–80 | 1.564 | 0.066 | 0.199 | 0.298 | 0.374 |
| 80–100 | 1.573 | 0.067 | 0.200 | 0.300 | 0.372 |
| **Douglas Daly** | | | | | |
| 0–15 | 1.554 | 0.045 | 0.090 | 0.311 | 0.383 |
| 15–30 | 1.768 | 0.074 | 0.093 | 0.253 | 0.303 |
| 30–60 | 1.589 | 0.197 | 0.197 | 0.320 | 0.370 |
| 60–90 | 1.719 | 0.197 | 0.197 | 0.271 | 0.321 |
| 90–120 | 1.635 | 0.197 | 0.197 | 0.250 | 0.353 |

the difference between observed and modeled values against the average of these two values. This visualizes if there is any relationship between the difference between observed and modeled values and the overall magnitude of these values. These plots also include, as horizontal lines, the mean difference between observed and modeled values and two standard deviations above and below the mean (referred to as the limits of agreement). Based on the guidance provided in Tedeschi (2006), a statistical evaluation of model performance was undertaken by calculating the coefficient of determination ($R^2$; the amount of variance accounted by a linear regression is fitted to the data), concordance correlation coefficient (CCC; a simultaneous measure of accuracy and precision of the model), residual mean square error (RMSE; a measure of the spread in the residual errors), mean bias (the average difference between the observed values and modeled values), and bias correction factor (an indication as to the agreement between the line of best fit and a 1:1 line) for the relationship between observed and modeled data. To assess if model performance was influenced by the availability of water or N (as a method to assess the performance of the soil module in supplying these resources), the difference between modeled and observed values was color scaled and then plotted against the model stress factors for the impact of N stress on the *x* axis and water stress on the *y* axis. To assess if the results of extreme weather events (such as lodging, leaching, and disease from intense rainfall and heat stress, pollen sterility, and high water use) influenced the deviation of the model from observed yields, daily rainfall and temperature values were plotted against the difference between the modeled and observed yields. All graphical and statistical analyses were undertaken using R version 4.2.0 (R Core Team, 2022) with the *epiR* (Stevenson et al., 2022), *colourvalues* (Cooley, 2020), and *viridis* (Garnier et al., 2021) packages.

## 3 | RESULTS

### 3.1 | Model performance for individual crops

The plots presented in Figure 2 show that sorghum yield was reasonably well predicted for the limited ($n = 3$) dataset from Katherine. The data points from Douglas Daly were clustered between observed yields of 2.5 and 5.0 t/ha and modeled yields of 4.5 and 5.5 t/ha. This highlights a general overprediction of sorghum yield for this location with a generally low $R^2$, CCC, and bias correction, a mean bias of −1.0 t/ha, and

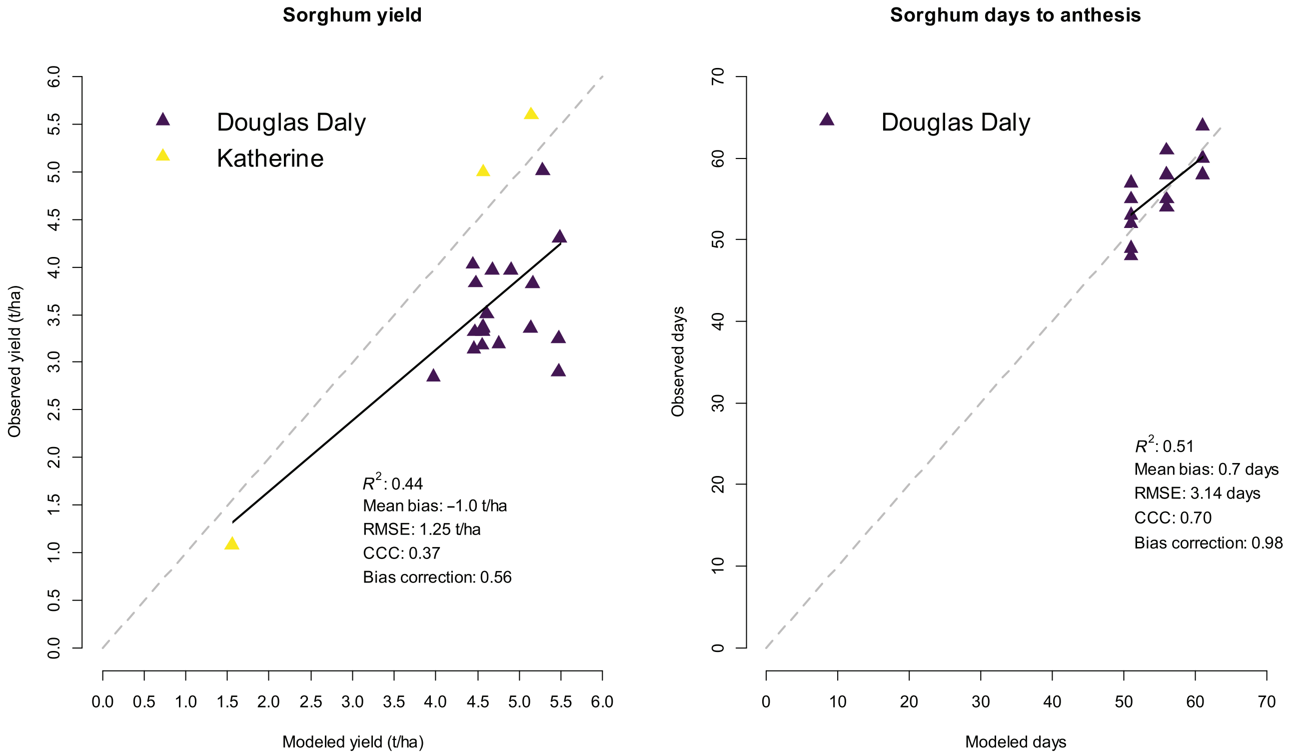


**FIGURE 2** Modeled versus observed sorghum yield and days to anthesis in the Northern Territory of Australia. The broken diagonal line represents 1:1 fit (i.e., $y = x$) while the solid line represents the line of best fit between the modeled data observed data. CCC, concordance correlation coefficient; RMSE, residual mean square error.

an RMSE greater than 1 t/ha. While there was a limited range in sorghum phenology observations in the datasets, a general good agreement was observed between modeled and observed days from sowing to anthesis. This resulted in a CCC of 0.7 and a bias correction of 0.98. As indicated by the mean bias on average, the model values were 0.70 days behind the observed days to anthesis.

While there was general agreement between observed and modeled yields for soybean, there was considerable variation around the 1:1 fit (Figure 3). This resulted in a $R^2$, RMSE, CCC, and bias correction of 0.48, 0.81, 0.63, and 0.90 t/ha, respectively. Soybean yield was generally overpredicted with a mean bias of −0.40 t/ha. Days from sowing to anthesis of soybeans were predicted with marginal accuracy. The primary driver of this were two very late maturing cultivars. For these two cultivars, the model predicted 80 days from sowing to maturity where they were ca. 50 days to achieve anthesis. These two simulations were associated with exposure to water stress (see below). This resulted in an average overprediction of days to anthesis of 3.6 days. When these two data points were excluded from the analysis, the validation statistics were improved to an $R^2$ of 0.97, a mean bias of −0.2 days, an RMSE of 1.04 days, a CCC of 0.98, and a bias correction of 1.0. Interestingly, despite this deviation in days from sowing to anthesis for these two cultivars, the model predicted their days to maturity with an acceptable accuracy. There was a considerable improvement in the summary statistics for soybean days to maturity compared to days to anthesis with $R^2$ increasing from 0.77 to 0.89, RSME decreasing from 9.25 to 5.7 days, the CCC increasing from 0.68 to 0.90, and the bias correction increasing from 0.77 to 0.96.

Maize yield was well predicted across both the Katherine and Douglas Daly locations (Figure 4). This was reflected in the summary statistics with an $R^2$ of 0.77, an RSME of 1.82 t/ha, a CCC of 0.86, a mean bias of 0.4 t/ha, and a bias correction of 0.8. Points at the lower end of the graph (less than 6 t/ha of modeled yield) exclusively came from experiments with relatively low N fertilizer applications (less than 180 kg N/ha) while the points at the higher end of the graph came from experiments with high levels of N fertilizer use (greater than 230 kg N/ha). There was a limited number ($n = 5$) of observations for mungbean yield but the model was able to capture the yield differences between the Katherine and Douglas Daly locations (Figure 4).

Rice yield was well predicted across both the Katherine and Tortilla Flats locations (Figure 5). The data points from Katherine were clustered between 2 and 4 t/ha (for both the observed and predicted values), while there was a greater range in the data points for Tortilla Flats. The summary statistics for rice yield confirmed an acceptable agreement between observed and modeled values with an $R^2$ of 0.81, a CCC of 0.74, a mean bias of 0.3 t/ha, and a bias correction of 0.93,

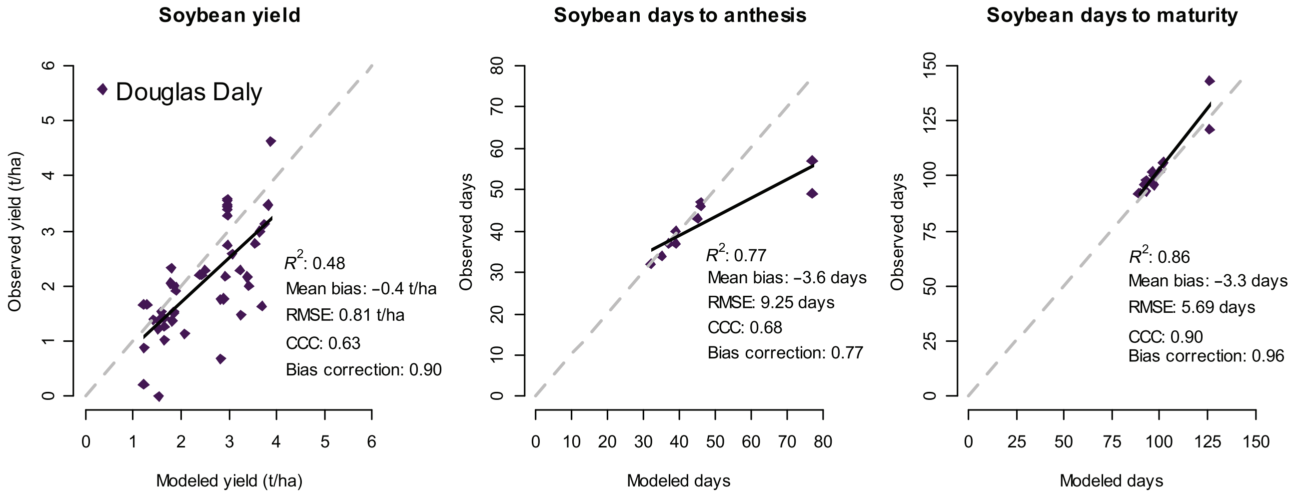


**FIGURE 3** Modeled versus observed soybean yield, days to anthesis and days to maturity in the Northern Territory of Australia. The broken diagonal line represents 1:1 fit (i.e., $y = x$) while the solid line represents the line of best fit between the modeled data observed data. CCC, concordance correlation coefficient; RMSE, residual mean square error.

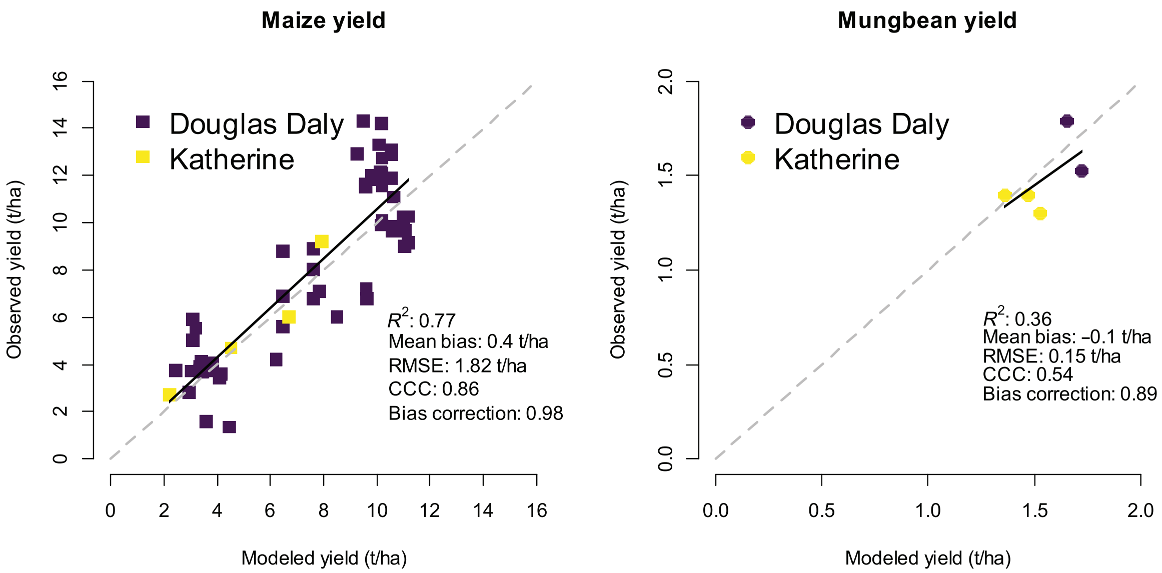


**FIGURE 4** Modeled versus observed yield of maize and mungbeans grown in the Northern Territory of Australia. The broken diagonal line represents 1:1 fit (i.e., $y = x$) while the solid line represents the line of best fit between the modeled data observed data. CCC, concordance correlation coefficient; RMSE, residual mean square error.

despite a high RMSE of 1.45 t/ha. A similar relationship between observations and modeled values was also present for rice biomass, despite some data points for Katherine clustered at the lower end of the range of biomass observations (Figure 5). Summary statistics for rice biomass were an $R^2$ of 0.76, an RMSE of 2.31 t/ha, a CCC of 0.87, a mean bias of 0.3 t/ha, and a bias correction of 0.99. The days from sowing to maturity for rice was well predicted for Tortilla Flats. However, for Katherine, the days from sowing to maturity was generally underpredicted. This resulted in overall summary statistics of an $R^2$ of 0.81, an RSME of 21.9 days, a CCC of 0.91, a mean bias of 14.7 days, and a bias correction of 0.67.

The Bland and Altman plot for crop yields (Figure 6) is suggestive of specific conditions where model performance may be less than an ideal optimum. Specifically, there were four high-yielding maize crops (>13.1 t/ha) that were present in the dataset (grown at Douglas Daly) and two high-yielding rice crops (>9.7 t/ha) at Tortilla Flats. These instances fell on the lower side of the limits of agreement (two standard deviations from the mean difference between modeled and observed values). There were also three instances of the difference between modeled and observed rice biomass being less than the limit of agreement. However, unlike for yield, these seemed unrelated to the magnitude of biomass.

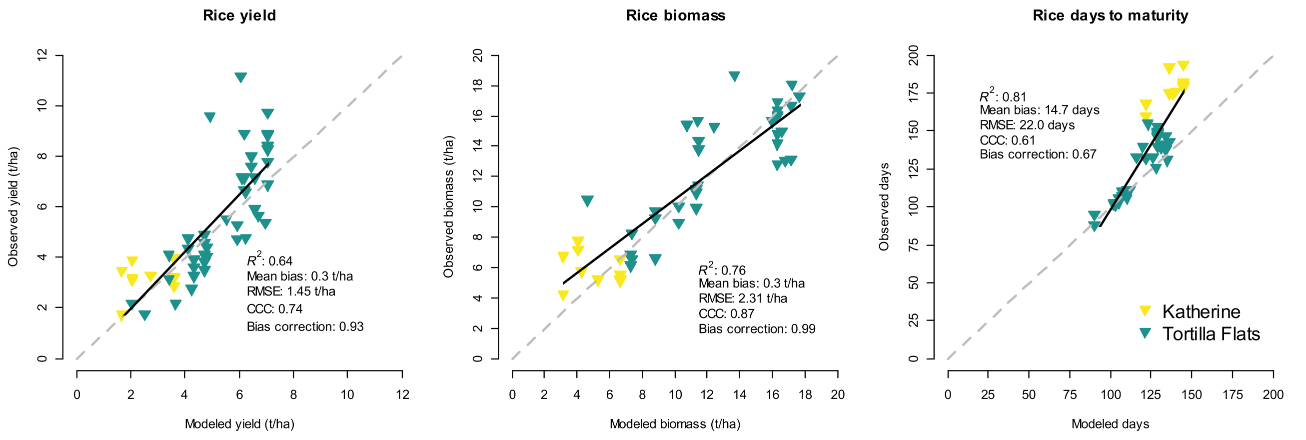


**FIGURE 5** Modeled versus observed rice yield, biomass and days to maturity in the Northern Territory of Australia. The broken diagonal line represents 1:1 fit (i.e., $y = x$) while the solid line represents the line of best fit between the modeled data observed data. CCC, concordance correlation coefficient; RMSE, residual mean square error.

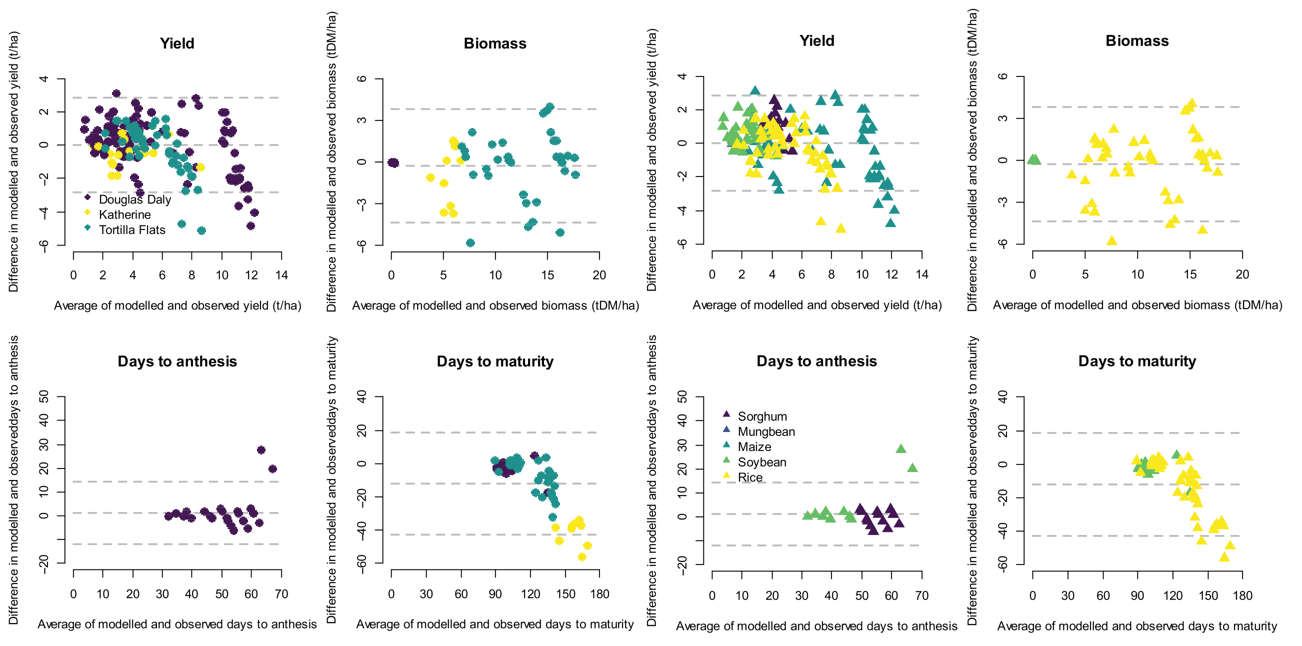


**FIGURE 6** Bland–Altman plots for yield, biomass, days to anthesis and days to maturity of sorghum, maize, rice, soybean, and mungbean grown at Douglas Daly, Katherine, and Tortilla Flats the Northern Territory of Australia. The center broken line represents the mean difference between the modeled and observed values. The upper and lower broken lines represent the mean ± two standard deviations (referred to the limits of agreement).

The Bland and Altman plot (Figure 6) presented two observations for days from sowing to anthesis for soybeans that were considerably overpredicted by the model (Figure 3), being well over two standard deviations above the mean difference between the modeled and observed values. All other differences between modeled and observed values for days from sowing to anthesis were well within the two standard deviations from the mean. Between modeled and observed days to maturity, all the points for rice grown at Katherine were clustered either below two standard deviations from the mean or just above it.

## 3.2 | Influence of N and water stress on model performance

Nitrogen and water stress were present within the datasets used for this validation. When the stress factors were plotted with the difference between modeled and observed values as color-scaled scatter plots, there was no clear influence of the level of stress on the difference between the observed and modeled yield (Figures S1–S4). This means that the model was equally accurate in representing the yield of crops grown with or without these stressors. For biomass, observed data points were limited, and there were limited cases with N stress limiting crop growth. Similarly, for day to anthesis, there was a limited range in the level of water and N stress in the simulations, which limits any conclusions regarding a relationship between stress and model deviation from observed values. There were two points for soybeans (plotted over each other) where water stress was associated with a deviation in days to anthesis. For days to maturity, as N stress increased the deviation between observed and modeled also increased. Similarly, as water stress increased the difference between modeled and observed days to maturity increased. This may suggest that the model has reduced accuracy in predicting development and maturity dates for crops experiencing N or water deficit stress.

Across all the crops, there was no discernible impact from individual rainfall totals or maximum and minimum temperatures on the difference between modeled and observed yields (Figures S5 and S6). However, grouping all crops together hides the potential crop-specific trends. There was a discernible effect of temperatures on model accuracy for sorghum and rice (Figures S7 and S8). For both crops, exposure to cool temperatures during vegetative growth was associated with an underprediction of yield. For sorghum yield, there was a trend towards underprediction by the model with exposure to daily maximum temperatures less than 28˚C, particularly in the vegetative growth stages (Figure S7). For rice (Figure S8), an underprediction of yields was associated with exposure to maximum temperatures less than 26˚C and minimum temperatures less than 8˚C during the vegetative growth stages. For maize, mungbean, and soybean, there was also no discernible impact of individual daily maximum and minimum temperatures on the difference between modeled and observed yields (Figures S9–S11).

## 4 DISCUSSION

The results of this study for yield, phenology, and biomass are in agreement with other multisite analysis of the APSIM frameworks performance (e.g., Gaydon et al., 2017; Pembleton et al., 2013; Ojeda et al., 2018; Radanielson et al., 2018). Compared to the analysis presented in Carberry et al. (1996), the agreement between observed and modeled values was lower in our analysis. However, there were some key differences between the approaches that needed to be highlighted. These are as follows:

1. Our analysis covered an additional two locations (Douglas Daly and Tortilla Flats) and three additional crops (rice, soybean, and mungbean).
2. Our analysis used predicted soil properties sourced from a general description of major agricultural soils in the Northern Territory (Hill et al., 2011) as opposed to directly measured soil properties from each experiment.

The second point adds a level of uncertainty to our analysis that is not present in other APSIM validations and testing studies. However, this level of uncertainty exists in the current and recent applications of APSIM in the Northern Territory (CSIRO, 2018), and it is important to test the model under similar levels of uncertainty. The reduction in agreement between the two studies should not be interpreted as a reduction in model performance over time. Our study is also the first to evaluate the capacity of APSIM 7.10 to simulate rice, soybean, and mungbean in the Northern Territory. Our results for rice and soybeans for the most part are promising with yield and phenology well predicted across a wide range of maturity types. This is testament to the robustness of the science behind the APSIM modeling framework components as described in Robertson and Carberry (1998), Robertson et al. (2002), and Gaydon et al. (2017). The two instances where there was deviation between the modeled and observed values for soybean days to anthesis were associated with water deficit stress. The addition of a water stress modifier to the chickpea (*Cicer arietinum* L.) model has been shown to improve model performance (Chauhan et al., 2019). Given the similar model structures of chickpea and soybean (Robertson et al., 2002), adding similar modifiers to soybeans could improve this result.

The model deviation for yield occurred in high-yielding maize and rice crops events with the model underpredicting yield (Figure 6). Assuming there was no error in the measurements associated with the yield data, this may suggest that the model's equations and parametrization were unable to fully capture crop growth and soil processes for the specific situations of a high production potential. Archontoulis et al. (2020) found that APSIM was able to capture the high yields of soybean grown in Iowa. As soybean in APSIM is not reliant on the soil to supply N, this suggests that the errors observed in the current study may be due to the soil N component of the model. This is not surprising considering APSIM's pedigree in dryland, low-input systems (McCown et al., 1996). The deviation for crop phenology for the different crops studied was associated with N and water stress in the simulations (Figures S3 and S4), highlighting potential limitations are the ability of APSIM to represent the effect of N and water stress on crop phenology. In most crop model representations, crop phenology is mainly driven by thermal time accumulation and cultivar-specific parameters with limited mechanistic adjustments made from nutrient and water stress. Predicting phenology accurately is key to predicting yield accurately (Chauhan et al., 2019), improving the models' representation of stress effects on development should be a key focus of development and improvement efforts.

In this analysis, we observed no impact on extreme weather that is commonly experienced in tropical environments such as rainfall (and its potential impacts on lodging, disease, and nutrient leaching) or high-temperature events (and its potential impact through heat stress, pollen sterility, and high water use). While many crop models are acknowledged to not fully capture the impacts of weather extremes (Rötter et al., 2018), this result (albeit with a limited dataset) suggests that within the limits of these extremes as they are experienced in the Northern Territory, APSIM can capture these impacts. Interestingly, the exposure to cooler temperature during vegetative growth was associated with an underprediction of yield for rice and sorghum; however, these temperatures would not be considered extreme. Both the rice (Li et al., 2017) and sorghum (Hammer & Muchow, 1994) models have a different model structure and approaches compared to the maize (Carberry et al., 1989), soybean, and mungbean (Robertson et al., 2002) models. Recent efforts by the APSIM initiative (www.APSIM.info) to update the APSIM framework and standardize the crop model development process called APSIM next generation (D. Holzworth et al., 2018) and the plant modeling framework (Brown et al., 2014) are making a significant contribution to facilitate and invest efforts in the area of model improvement and standardization, which will ultimately address the N stress, water stress, and low temperature limitations that we have identified. A recent example of this is demonstrated in Pasley et al. (2023), which has improved the representation of mungbeans in APSIM next gen across a range of environments including the Northern Territory.

## 5 | CONCLUSION

The overall acceptable performance of the APSIM framework in this regional-level validation analysis provides confidence that the model and its derivative decision support tools can be used with confidence to aid and guide the expansion and diversification of a field cropping industry in the Northern Territory of Australia. These tools when used by growers, advisors, and government will aid in de-risking the transition from pastoral agriculture to crop production and will provide confidence to those investing in the expansion of the sector. Through our analysis, we have identified areas for model improvement, specifically the simulation of high-yielding crops, the impacts of low temperatures, and the impacts of N and water stress on crop phenology in tropical environments. The impact of high rainfall and temperature events on yield was appropriately captured. Further efforts to validate other rotation crops such as chickpeas and peanuts would also be of considerable value as these are crops that have also been identified as having a potential role in future Northern Territory farming systems (Ash et al., 2017). This future work will require field experimentation where the use of data for model validation is a key design consideration.

## AUTHOR CONTRIBUTIONS

**Keith G. Pembleton**: Conceptualization; methodology; investigation; data curation; formal analysis; visualization; writing—original draft; funding acquisition. **Ando M. Radanielson**: Conceptualization; methodology; investigation; data curation; writing—review and editing.

## ACKNOWLEDGMENTS

This work was funded by the Cooperative Research Centre for Developing Northern Australia (CRCNA), which is part of the Australian Government's Cooperative Research Centre Program (CRCP). The CRCNA also acknowledges the financial and in-kind support of the project participants. Acknowledgment is made of the APSIM Initiative, which takes responsibility for quality assurance, and a structured innovation program for APSIM's modeling software, which is provided free for research and development use (see www.apsim.info for details).

## CONFLICT OF INTEREST STATEMENT

Keith G. Pembleton represents the University of Southern Queensland on the APSIM Initiative's steering committee. The APSIM Initiative takes responsibility for quality assurance and a structured innovation program for the APSIM model. Ando M. Radanielson declares no conflict of interests

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## REFERENCES

Archontoulis, S. V., Castellano, M. J., Licht, M. A., Nichols, V., Baum, M., Huber, I., Martinez-Feria, R., Puntel, L., Ordóñez, R. A., Iqbal, J., Wright, E. E., Dietzel, R. N., Helmers, M., Vanloocke, A., Liebman, M., Hatfield, J. L., Herzmann, D., Córdova, S. C., Edmonds, P., … Lamkey, K. R. (2020). Predicting crop yields and soil-plant nitrogen dynamics in the US Corn Belt. *Crop Science*, *60*, 721–738. https://doi.org/10.1002/csc2.20039

Ash, A., Gleeson, T., Hall, M., Higgins, A., Hopwood, G., Macleod, N., Paini, D., Poulton, P., Prestwidge, D., Webster, T., & Wilson, P. (2017). Irrigated agricultural development in northern Australia: Value-chain challenges and opportunities. *Agricultural Systems*, *155*, 116–125. https://doi.org/10.1016/j.agsy.2017.04.010

Bellocchi, G., Rivington, M., Donatelli, M., & Matthews, K. (2010). Validation of biophysical models: Issues and methodologies. A review.

*Agronomy for Sustainable Development*, *30*, 109–130. https://doi.org/10.1051/agro/2009001

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. *Environmental Modelling and Software*, *62*, 385–398. https://doi.org/10.1016/j.envsoft.2014.09.005

Carberry, P. S., McCown, R. I., Muchow, R. C., Dimes, J. P., Probert, M. E., Poulton, P. I., & Dalgliesh, N. P. (1996). Simulation of a legume ley farming system in northern Australia using the Agricultural Production Systems Simulator. *Australian Journal of Experimental Agriculture*, *36*, 1037–1048. https://doi.org/10.1071/EA9961037

Carberry, P. S., Muchow, R. C., & McCown, R. L. (1989). Testing the CERES-Maize simulation model in a semi-arid tropical environment. *Field Crops Research*, *20*, 297–315. https://doi.org/10.1016/0378-4290(89)90072-5

Chapman, A. I., Sturtz, J. D., Cogle, A. I., Mollah, W. S., & Bateman, R. J. (1996). Farming systems in the Australian semi-arid tropics—A recent history. *Australian Journal of Experimental Agriculture*, *36*, 915–928. https://doi.org/10.1071/EA9960915

Chauhan, Y. S., Ryan, M., Chandra, S., & Sadras, V. O. (2019). Accounting for soil moisture improves prediction of flowering time in chickpea and wheat. *Scientific Reports*, *9*, 7510. https://doi.org/10.1038/s41598-019-43848-6

Cook, G. (2009). Historical perspectives on land use development in northern Australia: With emphasis on the Northern Territory. In P. Stone (Ed.), *Northern Australian Land and Water Science Review 2009*. Northern Australia Land and Water Taskforce and CSIRO.

Cooley, D. (2020). *colourvalues* (R package version 0.3.7) [Computer software]. CRAN. https://CRAN.R-project.org/package=colourvalues

CSIRO. (2009). *Summary of reports to the Australian Government from the CSIRO Northern Australia sustainable yields project*. CSIRO.

CSIRO. (2018). *Water resource assessment for the Darwin catchments: An overview report to the Australian Government from the CSIRO Northern Australia Water Resource Assessment, part of the National Water Infrastructure Development Fund: Water Resource Assessments*. CSIRO.

Dimes, J. P., McCown, R. I., & Saffigna, P. G. (1996). Nitrogen supply to no-tillage crops, as influenced by mulch type, soil type and season, following pasture leys in the semi-arid tropics. *Australian Journal of Experimental Agriculture*, *36*, 937–946. https://doi.org/10.1071/EA9960937

Eastick, R., Hartley, N., Bennett, M., & Hearnden, M. (2012). Rice germplasm selection and production systems for the Northern Territory. In *Capturing opportunities and overcoming obstacles in Australian agronomy: Proceedings of the 16th ASA Conference*. Australian Society of Agronomy.

Garnier, S., Ross, N., Rudis, R., Camargo, A. P., Sciaini, M., & Scherer, C. (2021). *Rvision—Colorblind-Friendly Color Maps for R* (R package version 0.6.2) [Computer software]. CRAN. https://CRAN.R-project.org/package=viridis

Garside, A. L., & Buchanan, D. A. (n.d.). *Soybean research in the Northern Territory 1980–1985* (Technical Bulletin No. 130, Agdex 162/90). Northern Territory Division of Primary Producion.

Gaydon, D. S., Balwinder-Singh, Wang, E., Poulton, P. L., Ahmad, B., Ahmed, F., Akhter, S., Ali, I., Amarasingha, R., Chaki, A. K., Chen, C., Choudhury, B. U., Darai, R., Das, A., Hochman, Z., Horan, H., Hosang, E. Y., Kumar, P. V., Khan, A. S. M. M. R., … Roth, C. H. (2017). Evaluation of the APSIM model in cropping systems of Asia. *Field Crops Research*, *204*, 52–75. https://doi.org/10.1016/j.fcr.2016.12.015

Gaydon, D. S., Radanielson, A. M., Chaki, A. K., Sarker, M. M. R., Rahman, M. A., Rashid, M. H., Kabir, M. J., Khan, A. S. M. M. R., Gaydon, E. R., & Roth, C. H. (2021). Options for increasing Boro rice production in the saline coastal zone of Bangladesh. *Field Crops Research*, *264*, 108089. https://doi.org/10.1016/j.fcr.2021.108089

Hammer, G. L., & Muchow, R. C. (1994). Assessing climatic risk to sorghum production in water-limited subtropical environments I. Development and testing of a simulation model. *Field Crops Research*, *36*, 221–234. https://doi.org/10.1016/0378-4290(94)90114-7

Hill, J., Edmeades, B. F., Owens, G., & Hignett, C. (2011). *Plant industry soils of the Northern Territory: A Northern Territory companion to the healthy soils for sustainable vegetable farms: Ute guide*. Natural Resources Division, Department of Natural Resources, Environment, The Arts and Sport, NT Government.

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., Peake, A. S., Poulton, P. L., & McClelland, T. (2009). Re-inventing model-based decision support with Australian dryland farmers. 4. Yield Prophet® helps farmers monitor and manage crops in a variable climate. *Crop and Pasture Science*, *60*, 1057–1070. https://doi.org/10.1071/CP09020

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. *Environmental Modelling and Software*, *103*, 43–51. https://doi.org/10.1016/j.envsoft.2018.02.002

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., Moore, A. D., Brown, H., Whish, J. P. M., Verrall, S., Fainges, J., Bell, L. W., Peake, A. S., Poulton, P. L., Hochman, Z., … Keating, B. A. (2014). APSIM—Evolution towards a new generation of agricultural systems simulation. *Environmental Modelling and Software*, *62*, 327–350. https://doi.org/10.1016/j.envsoft.2014.07.009

Jeffrey, S. J., Carter, J. O., Moodie, K. B., & Beswick, A. R. (2001). Using spatial interpolation to construct a comprehensive archive of Australian climate data. *Environmental Modelling and Software*, *16*, 309–330. https://doi.org/10.1016/S1364-8152(01)00008-1

Jones, R. K., Probert, M. E., Dalgliesh, N. P., & Mccown, R. I. (1996). Nitrogen inputs from a pasture legume in rotations with cereals in the semi-arid tropics of northern Australia: Experimentation and modelling on a clay loam soil. *Australian Journal of Experimental Agriculture*, *36*, 985–994. https://doi.org/10.1071/EA9960985

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., … Smith, C. J (2003). An overview of APSIM, a model designed for farming systems simulation. *European Journal of Agronomy*, *18*, 267–288. https://doi.org/10.1016/S1161-0301(02)00108-9

Kisaka, M. O., Mucheru-Muna, M., Ngetich, F. K., Mugwe, J. N., Mugendi, D. N., Mairura, F., & Muriuki, J. (2016). Using APSIM-model as a decision-support-tool for long-term integrated-nitrogen-management and maize productivity under semi-arid conditions in Kenya. *Experimental Agriculture*, *52*, 279–299. https://doi.org/10.1017/S0014479715000095

Li, T., Angeles, O., Marcaida, M., Manalo, E., Manalili, M. P., Radanielson, A., & Mohanty, S. (2017). From ORYZA2000 to ORYZA (v3): An improved simulation model for rice in drought and nitrogen-deficient environments. *Agriculture Forrest Meteorology*, *237–238*, 246–256. https://doi.org/10.1016/j.agrformet.2017.02.025

Martin Bland, J., & Altman, D. (1986). Statistical methods for assessing agreement between two methods of clinical measurement. *Lancet*, *327*, 307–310. https://doi.org/10.1016/S0140-6736(86)90837-8

Mccown, R. L (2002). Changing systems for supporting farmers' decisions: Problems, paradigms, and prospects. *Agricultural Systems*, *74*, 179–220. https://doi.org/10.1016/S0308-521X(02)00026-4

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, model testing and simulation in agricultural systems research. *Agricultural Systems*, *50*, 255–271. https://doi.org/10.1016/0308-521X(94)00055-V

Meier, E. A., & Thorburn, P. J. (2016). Long term sugarcane crop residue retention offers limited potential to reduce nitrogen fertilizer rates in Australian wet tropical environments. *Frontiers in Plant Science*, *7*, 1017. https://doi.org/10.3389/fpls.2016.01017

Morel, J., Kumar, U., Ahmed, M., Bergkvist, G., Lana, M., Halling, M., & Parsons, D. (2021). Quantification of the impact of temperature, CO2, and rainfall changes on Swedish annual crops production using the APSIM model. *Frontiers in Sustainable Food Systems*, *5*, 665025. https://doi.org/10.3389/fsufs.2021.665025

Muchow, R. C. (1989). Comparative productivity of maize, sorghum and pearl millet in a semi-add tropical environment. I. Yield potential. *Field Crops Research*, *20*, 191–205. https://doi.org/10.1016/0378-4290(89)90079-8

Muchow, R. C. (1990). Effect of nitrogen on partitioning and yield in grain sorghum under differing environmental conditions in the semi-arid tropics. *Field Crops Research*, *25*, 265–278. https://doi.org/10.1016/0378-4290(90)90009-Z

Northern Australia Land and Water Taskforce. (2009). Sustainable development of northern Australia*,* A report to Government from the Northern Australia Land and Water Taskforce. Department of Infrastructure, Transport, Regional Development and Local Government.

O'Gara, F. (2007). *Irrigated maize production in the top end of the Northern Territory: Production guidelines and research results* (Technical Bulletin No. 326). Northern Territory Government Department of Primary Industry, Fisheries and Mines.

Ojeda, J. J., Pembleton, K. G., Caviglia, O. P., Islam, M. R., Agnusdei, M. G., & Garcia, S. C. (2018). Modelling forage yield and water productivity of continuous crop sequences in the Argentinian Pampas. *European Journal of Agronomy*, *92*, 84–96. https://doi.org/10.1016/j.eja.2017.10.004

Pasley, H., Wenham, K., Bell, L., Huth, N., Holzworth, D., Chaki, A., Gaydon, D., & Collins, M. (2023). APSIM next generation mungbean model: A tool for advancing mungbean production. *Field Crops Research*, *298*, 108955. https://doi.org/10.1016/j.fcr.2023.108955

Pembleton, K. G., Cullen, B. R., Rawnsley, R. P., Harrison, M. T., & Ramilan, T. (2016). Modelling the resilience of forage crop production to future climate change in the dairy regions of South-eastern Australia using APSIM. *Journal of Agricultural Science*, *154*, 1131–1152. https://doi.org/10.1017/S0021859615001185

Pembleton, K. G., Cullen, B. R., Rawnsley, R. P., & Ramilan, T. (2020). Climate change effects on pasture-based dairy systems in south-eastern Australia. *Crop and Pasture Science*, *72*, 666–677. https://doi.org/10.1071/CP20108

Pembleton, K. G., Rawnsley, R. P., Jacobs, J. L., Mickan, F. J., O'brien, G. N., Cullen, B. R., & Ramilan, T. (2013). Evaluating the accuracy of the Agricultural Production Systems Simulator (APSIM) simulating growth, development, and herbage nutritive characteristics of forage crops grown in the south-eastern dairy regions of Australia. *Crop and Pasture Science*, *64*, 147–164. https://doi.org/10.1071/CP12372

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., & Mohammed, C. L. (2018). Advancing a farmer decision support tool for agronomic decisions on rainfed and irrigated wheat cropping in Tasmania. *Agricultural Systems*, *167*, 113–124. https://doi.org/10.1016/j.agsy.2018.09.003

Piñeiro, G., Perelman, S., Guerschman, J. P., & Paruelo, J. M. (2008). How to evaluate models: Observed vs. predicted or predicted vs. observed? *Ecological Modelling*, *216*, 316–322. https://doi.org/10.1016/j.ecolmodel.2008.05.006

Probert, M. E., Carberry, P. S., Mccown, R. L., & Turpin, J. E. (1998). Simulation of legume-cereal systems using APSIM. *Australian Journal of Agricultural Research*, *49*, 317–328. https://doi.org/10.1071/A97070

R Core Team. (2022). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. https://www.R-project.org/

Radanielson, A. M., Gaydon, D. S., Li, T., Angeles, O., & Roth, C. H. (2018). Modeling salinity effect on rice growth and grain yield with ORYZA v3 and APSIM-Oryza. *European Journal of Agronomy*, *100*, 44–55. https://doi.org/10.1016/j.eja.2018.01.015

Rhebergen, T., & Yeates, S. J. (2023). Climate and soil-based constraints to rainfed cotton yield in the Northern Territory, Australia—A modelling approach using APSIM-OZCOT. *European Journal of Agronomy*, *151*, 126998. https://doi.org/10.1016/j.eja.2023.126998

Robertson, M. J., & Carberry, P. S. (1998, September 15–17). *Simulating growth and development of soybean in APSIM* [Conference presentation]. Tenth Australian Soybean Conference, Brisbane, Australia.

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. *Australian Journal of Agricultural Research*, *53*, 429–446. https://doi.org/10.1071/AR01106

Rötter, R. P., Appiah, M., Fichtler, E., Kersebaum, K. C., Trnka, M., & Hoffmann, M. P. (2018). Linking modelling and experimentation to better capture crop impacts of agroclimatic extremes—A review. *Field Crops Research*, *221*, 142–156. https://doi.org/10.1016/j.fcr.2018.02.023

Shotton, P. (2000). *Grain sorghum variety evaluation trials for the Douglas Daly District, NT* (Agdec No: 115/34). Northern Territory Department of Primary Industry and Fisheries.

Shukr, H. H., Pembleton, K. G., Zull, A. F., & Cockfield, G. J. (2021). Impacts of effects of deficit irrigation strategy on water use efficiency and yield in cotton under different irrigation systems. *Agronomy*, *11*, 231. https://doi.org/10.3390/agronomy11020231

Sivapalan, S. (2016). *Agronomic options for profitable rice-based farming system in northern Australia* (Publication No. 16/048). Rural Industries Research and Development Corporation.

Stevenson, M., Sergeant, E., Nunes, T., Heuer, C., Marshall, J., Sanchez, J., Thornton, R., Reiczigel, J., Robison-Cox, J., Sebastiani, P., Solymos, P., Yoshida, K., Jones, G., Pirikahu, S., Firestone, S., Kyle, R., Popp, J., Jay, M., Reynard, C., … Rabiee, A. (2022). *epiR: Tools* *for the analysis of epidemiological data* (R package version 2.0.46). https://CRAN.R-project.org/package=epiR

Tedeschi, L. O. (2006). Assessment of the adequacy of mathematical models. *Agricultural Systems*, *89*, 225–247. https://doi.org/10.1016/j.agsy.2005.11.004

Thiagalingam, K., Dalgliesh, N. P., Gould, N. S., Mccown, R. I., Cogle, A. I., & Chapman, A. I. (1996). Comparison of no-tillage and conventional tillage in the development of sustainable farming systems in the semi-arid tropics. *Australian Journal of Experimental Agriculture*, *36*, 995–1002. https://doi.org/10.1071/EA9960995

Whitbread, A. M., Robertson, M. J., Carberry, P. S., & Dimes, J. P. (2010). How farming systems simulation can aid the development of more sustainable smallholder farming systems in southern Africa. *Australian Journal of Experimental Agriculture*, *32*, 51–58.

Wilson, P. L., Ringrose-Voase, A., Jacquier, D., Gregory, L., Webb, M., Wong, M. T. F., Powell, B., Brough, D., Hill, J., Lynch, B., Schoknecht, N., & Griffin, T. (2009). Land and soil resources in Northern Australia. In P. Stone (Ed.), *Northern Australia Land and Water Science Review full report—October 2009* (pp. 2-1–2-47). Office of Northern Australia.

Yeates, S. J., & Imrie, B. C. (1993). Mungbean development in the Northern Territory. In G. K. McDonald, & W. D. Bellotti (Eds.), *Proceedings of the 7th Australian Agronomy Conference* (pp. 84–87). The Australian Society of Agronomy.

## SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

**How to cite this article:** Pembleton, K. G., & Radanielson, A. M. (2024). Validating APSIM for the northern territory of Australia: An environment with challenging weather and soils. *Agronomy Journal*, *116*, 1357–1370. https://doi.org/10.1002/agj2.21567