Field Crops Research 275 (2022) 108344

Contents lists available at ScienceDirect

Field Crops Research

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

How we used APSIM to simulate conservation agriculture practices in the rice-wheat system of the Eastern Gangetic Plains

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ARTICLE INFO

Keywords:
Calibration
Validation
Zero tillage
Irrigation
Nitrogen

ABSTRACT

Examples of how to simulate performance of conservation agriculture (CA) and conventional tillage (CT) practices using cropping systems models are rare in the literature, and from the Eastern Gangetic Plains (EGP). Here we report a comprehensive evaluation of the capacity of APSIM for simulating the performance of CA and CT cropping practices under a diverse range of tillage (CT vs zero tillage (ZT)), crop establishment options (puddled transplanted rice vs unpuddled transplanted rice), residue, N rates, and irrigation practices from two sites in the EGP that differed in soil type, water table dynamics, and agro-climatic conditions. We followed a robust procedure of model parameterisation, calibration, and validation, then undertook statistical analyses to evaluate model performance. We have demonstrated that when different values for key model input parameters are employed (i.e. change in soil properties (Ks, BD)), crop rooting parameters (xf- root hospitality, kl- root extraction efficiency) and soil microorganism activity (F_{biom}- fraction of soil organic matter present as microbial biomass and F_{inert}- the inert fraction of soil organic matter), the model performed well in simulating the different performances of CA and CT management practices across the environments in the EGP. Model performance was markedly better in the full-N than in zero-N, but both are still considered acceptable. In addition to well-watered and fertilised treatments, the model was able to capture an observed crop failure in rainfed unpuddled transplanted rice accurately, illustrating an ability to capture crop response under a wide range of water stress environments. As demonstrated by robust statistical criteria, APSIM was able to capture the effect of cropping system, irrigation, tillage, residue, and N-application rate within the bounds of experimental uncertainty, hence is now deemed a suitable tool for scenario analyses around the relevant practices.

1. Introduction

The rice-wheat cropping system plays a major food security role, occupying around 12.4 Mha in four south Asian countries (India, Pakistan, Nepal, and Bangladesh) (Timsina et al., 2010) and producing staple food for 15% of the world's population (Laik et al., 2014). There is a growing awareness among policymakers and people of the area of the need to increase the productivity of the rice-wheat system, to meet the demand of the ever-growing population of the region while utilizing resources efficiently (Dobermann and Witt, 2000; Ladha et al., 2009; Hochman et al., 2013). Intensification of current rice-wheat rotation (conventional puddled transplanted rice–conventional-till (CT) wheat), through the inclusion of a rainfed summer legume (mungbean) following wheat (Mondal et al., 2012; Islam et al., 2019), along with the implementation of conservation agriculture (CA) based management practices (Hobbs, 2007; Jat et al., 2020), could help overcome these major constraints and sustain productivity (Chaki et al., 2019a). The results of field experiments conducted in this regard, including the findings presented in Chaki (2021); Chaki et al. (2021a); Chaki et al. (2021b), provide insights into system performance over only short periods. Furthermore, given resource constraints, it is not possible to test the many possible variations to cropping practices, or to understand

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https://doi.org/10.1016/j.fcr.2021.108344
Received 12 October 2020; Received in revised form 13 September 2021; Accepted 27 October 2021
Available online 9 November 2021

systems behaviour/performance with new imposed practices over a broad range of growing season conditions. Cropping system models that are locally calibrated and validated using short-term experimental data and long-term climatic data, can be useful tools for investigating farming system intervention options including long-term system performance with respect to production, economics, environmental trade-offs, and resource use (Akhter et al., 2014; Amarasingha et al., 2015, 2017; Khaliq et al., 2019).

Simulation models are being increasingly used for analysis and decision making processes in agricultural fields, such as for achieving increased production and food security, understanding soil carbon changes, ecosystem services, limiting greenhouse gas emissions, climate change adaptation and mitigation, pests and disease losses, livestock and pasture production, and understanding climatic risk; all of which are not possible from short-term experiments (Holzworth et al., 2014a, 2014b). Many modelling efforts have continued over decades because of their potential benefits in agricultural decision support systems (Jones et al., 2003; Whitbread et al., 2010; Holzworth et al., 2014a). The biophysical models integrate soil, climate, crop, and management practices to simulate the growth and yield of a crop in association with below-ground processes (e.g., soil N dynamics, soil water), often on a daily time-step basis. Once properly parameterised, calibrated and validated, the model can be used to analyse the influence of a range of factors on the growth and yield of a crop, and also to interpret experimental findings and extrapolate to wider climatic, soil and management conditions. Furthermore, well-tested models help to understand numerous underlying processes of crop production and to quantify them, which is often difficult and expensive under field conditions. Several dynamic simulation models are being used worldwide such as DSSAT (Jones et al., 2003), APSIM (Keating et al., 2003; Holzworth et al., 2014a), CropSyst (Stöckle et al., 2003), EPIC (Izaurralde et al., 2006), STICS (Brisson et al., 2003), WOFOST (Keulen and Wolf, 1986), RIWER (Jing et al., 2010) and infoCrop (Aggarwal et al., 2006). However, few of them have the capacity to simulate farmer detailed management decisions which change from year to year based on prevailing climatic conditions or soil status (for example, different rice sowing dates each season based on start of monsoon rains), or to simulate the rice-based cropping systems (rice followed by non-rice crops in rotation) which dominate in the Eastern Gangetic Plains (EGP). The Agricultural Production Systems sIMulator (APSIM) is such a model and has been successfully used in modelling diversified cropping systems, crop rotations, intercropping, fallowing, water balance, N stress and balance, and environmental dynamics (Probert et al., 1997, 1998; Carberry et al., 2002; Keating et al., 2002; Robertson et al., 2002; Verburg and Bond, 2003; Whitbread et al., 2010; Balwinder-Singh et al., 2011; Akhter et al., 2014; Holzworth et al., 2014a; Chaki et al., 2019b). The model has also been improved to simulate rice-based cropping systems (Gaydon et al., 2012a). The capacity of APSIM to simulate major cropping systems of Asia (12 countries, various climates, soil, and management) has recently been evaluated successfully in terms of crop duration, growth, yield, crop sequences, water productivity, soil carbon changes and crop response to elevated CO_2 levels (Gaydon et al., 2017). No other cropping systems model offers the flexibility in specifying specific farmer decision making logic in simulations (Gaydon et al., 2017), thereby capturing season by season changes in farmer management practices in response to prevailing conditions. Although contrasts between CA vs CT practices are widely reported in the literature, there are very few examples of modelling these differences in cropping systems simulation (examples would be Balwinder-Singh et al. (2015), from the North-Western Indo Gangetic Plains (NW-IGP), and Corbeels et al. (2016), from Monze, Southern Province of Zambia) and there are none from the EGP. For simulating the impact of CA management on crop productivity, simulating soil water is the foremost variable (especially for water-limited environments) which should be simulated quite sensibly for the analysis of trade-offs of water allocation using the cropping systems model. To address this gap, we evaluated the capacity of APSIM to simulate the differences in observed performance between CA and CT cropping practices (which are illustrated in Fig. S1 by non 1:1 correlation relationships) with different N and irrigation managements in the rice-wheat system for two diverse environments (varied in soil types, water table dynamics, and agro-climatic conditions) of the EGP, utilising the data gained from experiments detailed in Chaki (2021); Chaki et al. (2021a); Chaki et al. (2021b).

2. Materials and methods

A robust procedure of model parameterisation, calibration, and validation was followed and then statistical analyses were undertaken to evaluate the model performance.

2.1. Description of the model used (APSIM v7.5)

The APSIM software provides a dynamic cropping systems modelling framework, which contains interconnected modules of key farming system components to be plugged in to simulate biophysical process in the systems (McCown et al., 1996; Keating et al., 2003; Holzworth et al., 2014a). The model comprises biophysical modules, a flexible management module, and various data input-output modules connected to a central simulation engine that drives the simulation of the systems.

The key strength of APSIM is that it focuses on cropping systems rather than individual crops, and simulates management-related contingencies between crops (e.g. planting dates) as well as carry-over effects on dynamic soil properties. Soil state variables are simulated continuously with regards to weather and management and crops “come to the soil finding it in one state and leave it in another state” after completing its term (McCown et al., 1995). APSIM places equal emphasis on the demand and supply sides of the simulation as impacted by weather and management, rather than being focussed on demand like many crop models.

The generic plant model incorporated into APSIM (Wang et al., 2002) has now been able to simulate 30 different crops (Holzworth et al., 2014a). The plant modules simulate key physiological processes on a daily time-step basis to simulate potential production which is constrained by the availability of resources (soil water, N), daily weather (solar radiation, maximum and minimum temperature, and rainfall) and management factors (sowing date, tillage type, irrigation, and N apply date, residue management, etc.) (Keating et al., 2003). Two model options are available for soil water balance simulation in APSIM - a cascading layer approach (SOILWAT: simple one using “tipping bucket” approach) (Probert et al., 1998) and Richards equation method (APSWIM: using numerical solution) (Verburg et al., 1996; Huth et al., 2012). The surface organic matter (SURFACEOM) module has the function of addition, removal, incorporation, decomposition in situ, and soil cover (Probert et al., 1998; Thorburn et al., 2001). APSIM simulates the effect of crop residues on the efficiency with which soil water is captured and retained in the system. APSIM calculates a surface residue effect (an overall effective cover value of 0–1) on soil evaporation and runoff based on the total residue present on the soil surface. The soil N (SOILN) module simulates the processes of nitrification and denitrification in the soil, stubble/roots left from the previous crop, and thus N supply to the plant (Probert et al., 1998). SOILN also simulates the soil carbon balance. APSIM treats soil organic matter as a three-pool system. The fresh organic matter (FOM) pool comprises the incorporated crop residues and roots. After decomposition of the FOM pool, the labile soil microbial biomass (BIOM) pool, and the more stable humus (HUM) pool are formed. The decomposition process of organic matter pools releases mineral N and the rates of mineralisation depend on soil temperature and water supply during the process (Probert et al., 1998). APSIM pond (POND) module simulates different biological and chemical processes occurring in the flooded rice field (Gaydon et al., 2012b).

2.2. Experimental sites

The field experiments were established on two experimental farms of the Bangladesh Wheat and Maize Research Institute (BWMRI); (i) in the Rajshahi district (latitude 24°22' N, longitude 88°39' E and 12 m ASL) and (ii) in the Dinajpur district (latitude 25°89' N, longitude 88°76' E and 41 m ASL). Each trial was conducted for two years (2016 and 2017 at Rajshahi, and 2017 and 2018 at Dinajpur) (Fig. 1). The Dinajpur site represents lighter soils (higher sand content) with deeper water tables, whereas the Rajshahi site represents heavy soils (high clay content) with shallow water tables. The details of climate, soil, and water table dynamics of the two sites are presented in Chaki et al. (2021a).

The experimental field had been under a conventionally-tilled rice-wheat system for the previous five years at Rajshahi and the previous twenty years at Dinajpur. However, mungbean was occasionally cultivated at the Rajshahi site between wheat and rice crops, practicing conventional methods.

2.3. Description of the experimental datasets

The details of the crop establishment, management, experimental measurements, cropping history, and data used for model calibration and validation has been described in Chaki (2021); Chaki et al. (2021a); Chaki et al. (2021b), and a summary of the experimental treatments are given here.

The experiment was laid out in a randomized split-plot design with three replications. The sub-plot size was 5 m × 6 m at Rajshahi and 3 m × 5 m at Dinajpur. The main plots were separated by a 1.2 m wide buffer, and sub-plots by 0.75 m buffer. Six cropping system treatments (CS) were allocated in the main plots as follows:

CS1: Puddled transplanted rice (PTR) – Conventional tilled wheat (CT wheat, 3 irrigations).

CS2: PTR – CT wheat (3 irrigations) – CT mungbean.

CS3: Unpuddled transplanted rice (UPTR) – ZT wheat (3 irrigations) – ZT mungbean.

CS4: UPTR – ZT wheat (2 irrigations) – ZT mungbean.

CS5: UPTR – ZT wheat (1 irrigation) – ZT mungbean.

CS6: Rainfed-unpuddled transplanted rice (RUPTR) – ZT wheat (0 irrigation) – ZT mungbean (Rainfed system).

Three N rates (N_0: zero N, N_{45}: 45 kg ha^{-1} N and N_{90}: 90 kg ha^{-1} N for rice, and N_0: zero N, N_{60}: 60 kg ha^{-1} N and N_{120}: 120 kg ha^{-1} N for wheat, representing zero, half, and full recommended application rate) were imposed in the sub-plots to assess model response to N, and its ability to simulate indigenous soil supply. There was no N fertiliser applied to mungbean. Rice was established as PTR (transplanted in puddled soil- a process of wet tillage in ponding water to create a soft soil environment and impermeable sub-soil layer) after CT wheat, and as UPTR (transplanted in no-till soil) after either ZT wheat or mungbean. Wheat was sown using a BARI ZT drill seeder into the conventionally tilled plot (land prepared by 2-W tractor) after PTR crop harvest, and into the no-till plot after UPTR and RUPTR crop harvest. Mungbean was sown after harvesting wheat using a similar method of establishment used in wheat. All above-ground crop residues were removed from the CT (CS1 and CS2), and 25 cm standing residue of rice and wheat and all residue of mungbean was retained in the CA (CS3 to CS6) after harvesting of the respective crops, following accepted CA practice (Islam et al., 2019).

2.4. APSIM parameterisation

The APSIM model (version 7.5) was parameterised by supplying measured data to the model such as climate data, soil properties, crop varieties, crop phenology, crop management practices followed, and inputs supplied.

2.4.1. Climate data

Daily maximum and minimum temperatures, rainfall, and solar radiation were recorded daily using an automatic weather station (DWS Decagon Weather Station configured with EM50 data logger at Rajshahi and HOBO RX3000 Weather Station at Dinajpur) installed at the

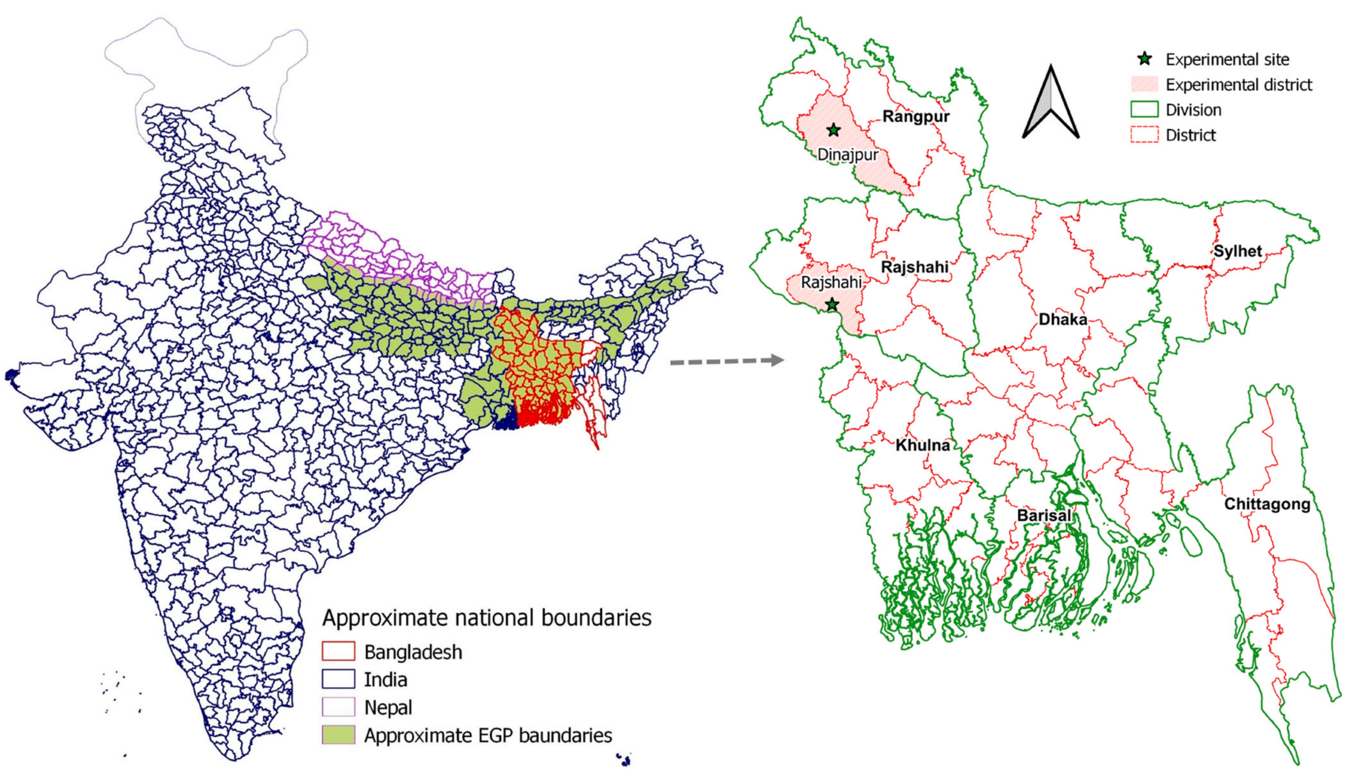

Fig. 1. Map showing experimental sites.

experimental sites. Long-term climate data (1982–2019) for Rajshahi and Dinajpur were collected from the weather records of the Bangladesh Meteorological Department (BMD) (Fig. S2). These data were used as climate inputs to APSIM.

2.4.2. Soils data

APSIM requires measurable soil physical parameters on a layer basis including bulk density, saturated water content, drained upper limit, lower limit (expressed in volumetric moisture content terms), soil water content (SWCON), and saturated hydraulic conductivity, and soil chemical parameters such as organic C, pH, and mineral N (NO_3^- and NH_4^+). Soil samples were collected from the experimental sites in seven layers: 0–15, 15–30, 30–60, 60–90, 90–120, 120–150, 150–180 cm and processed for particle size analysis, bulk density, and chemical composition using standard procedures (details in Chaki et al. (2021a)). Water content at the lower limit (at 1500 kPa) and drained upper limit (at 33 kPa) was measured using a pressure plate apparatus. Details of soil data used in APSIM simulations are provided in Table 1.

2.4.3. Groundwater levels

Groundwater levels were monitored at 15 days' interval in piezometer tubes installed in the experimental field at each site. At Rajshahi, the water table depth fluctuated between 0.5 m and 0.9 m during the *rabi* season, while it ranged from 0 to 1.6 m during the *Kharif* season (Fig. S3). The persistence of a shallow perched water table in the experimental field at Rajshahi indicated the presence of an impermeable layer restricting water movement through the soil profile. At Dinajpur, the water table depth was deeper than 2 m (2.5–4.7 m) during the *rabi* season, while it ranged from 1.5 to 4.8 m during the *Kharif* season (Fig. S3). The daily groundwater table depth data were provided as additional inputs to the APSIM climate file, and we configured APSIM manager logic to read this groundwater table data daily from the APSIM climate file.

2.5. APSIM calibration

APSIM requires some other parameters, such as crop genetic coefficients and some soil parameters that are difficult to measure or have greater uncertainty in measured values, which need iterative adjustment. Through the calibration process, the APSIM model was run with best possible guess values and then model outputs were compared with the first season of observed data (crop developmental stages, grain yield, biomass, soil water, soil NO_3^--N) from the selected treatments (details in subsections below), and the process repeated with re-estimated values until a satisfactory performance in simulating the output variables of interest (for example, yield) was achieved.

2.5.1. Crop phenology

The crop varieties used in this simulation study were rice (var. BRRI dhan52), wheat (var. BARI Gom-26 for Rajshahi, and BARI Gom-32 for Dinajpur) and mungbean (var. BARI Mung-6). For the rice variety, the simulated dates of sowing, transplanting, panicle initiation, flowering, physiological maturity, and harvest were compared with observed values to adjust the varietal rice phenology parameters for APSIM-Oryza. For the wheat varieties, the simulated (using APSIM-Wheat model) dates of sowing, emergence, flowering, physiological maturity, and harvest were compared with observed phenology dates for the first season, and similarly, model parameters adjusted until a good agreement was achieved. For the mungbean variety, the observed dates of sowing, emergence, flowering, physiological maturity, and harvest were compared with simulated phenology dates using the APSIM-Mungbean model. For each crop variety, the APSIM-crop phenology coefficient values were varied iteratively to produce a close match between the observed and simulated phenology dates.

The recommended irrigation and fertiliser treatment CS3N3 was selected for the calibration of phenology development parameters for wheat and mungbean. The APSIM-Oryza version was developed under non-limiting N environments and thus shows no effect of N-stress on rice phenology (Bouman and Van Laar, 2006; Gaydon et al., 2017). In order to capture the phenology dates of rice under different N-stress environments, treatments CS3N1, CS3N2, and CS3N3 were used to create different *virtual* varieties which exhibit correct phenology for the associated N treatment.

2.5.2. Crop biomass and yield

The biomass for rice was measured on plants collected from 4 hills (two hills × two hills) in each sub-plot at 35 days after transplanting (DAT), 60 DAT, 85 DAT, and at the maturity stage. The biomass for wheat and mungbean was measured on plants collected from a randomly located one-meter row in each sub-plot at 30 days after sowing (DAS), 50 DAS, 70 DAS, and at maturity stage for wheat, and at 30 DAS, 50 DAS, and at harvest for mungbean. The biomass was then split into leaves, stems, and heads for each treatment. The partitioned biomass was dried in an oven at 70 °C for 3–5 days until the weight was constant. At maturity, grain yield was measured by harvesting an area of 6 m^2 in the centre of each sub-plot. The grain was threshed using a plot

Table 1
Soil physical and chemical properties at the experimental sites.

Soil depth (cm)	pH	TOC (%)	NO_3^--N (mg kg^{-1})	NH_4^+-N (mg kg^{-1})	LL (cm^3 cm^{-3})	DUL (cm^3 cm^{-3})	SAT (cm^3 cm^{-3})	Ks (mm day^{-1})		BD (g cm^{-3})		Soil texture		
								CT	CA	CT	CA	Sand (%)	Silt (%)	Clay (%)
Rajshahi														
0–15	7.7	1.22	23.4	6.32	0.14	0.31	0.37	25.9	25.9	1.53	1.45	30	44	26
15–30	7.7	1.19	5.70	3.16	0.11	0.33	0.34	5.00	10.0	1.61	1.53	31	46	23
30–60	8.1	1.14	1.40	3.16	0.14	0.36	0.39	36.2	36.2	1.48	1.48	19	56	25
60–90	8.2	1.05	0.80	0.79	0.16	0.39	0.41	4.50	4.50	1.36	1.36	9	54	37
90–120	8.0	0.84	0.53	2.37	0.21	0.38	0.42	4.60	4.60	1.49	1.49	7	54	39
120–150	7.9	0.64	0.36	0.79	0.23	0.39	0.41	5.76	5.76	1.46	1.46	6	48	46
150–180	7.5	0.56	0.22	3.95	0.27	0.39	0.42	4.56	4.56	1.49	1.49	6	39	55
Dinajpur														
0–15	4.9	0.73	0.06	7.10	0.08	0.22	0.34	16.6	16.6	1.58	1.50	55	28	17
15–30	5.4	0.50	0.46	0.10	0.11	0.26	0.31	10.0	20.0	1.67	1.59	48	27	25
30–60	5.7	0.23	0.26	4.00	0.12	0.24	0.31	53.1	53.1	1.35	1.35	53	23	24
60–90	5.6	0.10	1.14	0.80	0.08	0.27	0.30	69.1	69.1	1.37	1.37	70	19	11
90–120	5.5	0.08	1.12	6.30	0.05	0.30	0.36	111	111	1.34	1.34	76	18	6
120–150	5.6	0.06	1.73	0.80	0.03	0.17	0.33	253	253	1.35	1.35	90	8	2
150–180	5.7	0.05	1.57	2.40	0.02	0.17	0.33	282	282	1.34	1.34	94	5	1

LL – volumetric water content at lower limit, DUL – volumetric water content at drained upper limit, SAT – volumetric water content at saturation, Ks – percolation rate, BD – bulk density, TOC – total organic carbon.

thresher and fresh grain weight was measured using a digital balance. Grain moisture content was determined by a grain moisture meter (model: GMK-303RS, Korea) for calculation of dry grain yield. Measured crop biomass partitioning data at different growth stages of rice, wheat, and mungbean growth were used to define assimilate partitioning ratios and their associated input parameters at different phenological stages.

2.5.3. Soil water content, and soil NO_3^--N measurements

Volumetric soil water content was determined on a daily basis using digital soil moisture sensors (model: GS1 dielectric soil moisture sensor, Decagon Devices Inc., USA) at 22.5 cm and 67.5 cm depths in 3 replicates of treatments with N_{120} sub-plots. This represented water dynamics of all the main treatments. The details of the soil water content data used for model evaluation have been described in detail in Chaki (2021).

In addition to this, soil samples were collected from the experimental sites in 3 replicates of treatments CS1N3, CS2N3, and CS3N3 in two layers (0–15 and 15–30 cm soil depth, 3 times during the wheat phase only) and processed for soil NO_3^--N measurements through colorimetric analysis of soil extracts (SEAL AQ2 + colorimetric analyser with cadmium reduction column) (APHA, 2017).

2.5.4. Adjustment of APSIM-Soils and APSIM-Manager specifications to represent CA vs CT

The initial soil condition was similar for both CT and CA treatments in these experiments. However, due to subsequent experimental interventions of different tillage, residue, and crop rotations, the soil conditions are expected to vary between CT and CA with time. Modifications to soil properties (particularly BD and Ks), crop rooting parameters (root hospitality factor (kl), and relative rate of root advance (xf)) and soil microorganism activity (the fraction of soil micro-organisms (F_{biom}) and inert humic material (F_{inert}) in soil organic matter (Probert et al., 1998)) were performed to better capture the CA environment.

2.5.4.1. Soil properties. Puddling in rice fields reduces the effective Ks and increases BD due to compaction and subsequent formation of a hard plough pan zone in a subsurface layer at around 20–30 cm depth (Sanchez, 1973; Humphreys et al., 1996; Kukal and Aggarwal, 2002). Due to practicing CA in the rice-wheat system, there is an increase of effective Ks and a decrease of BD with time in comparison with the CT system (Sharma et al., 2005; Gathala et al., 2011). Soil physical properties are treated as fixed system attributes in the current version of APSIM. To capture the tillage effect on soil property changes (Ks and BD), an increase of Ks (100%) and decrease of BD (5%) in CA compared with CT was specified in APSIM-SOIL according to the findings of Sharma et al. (2005) and Gathala et al. (2011). For the CT system, the Ks and BD values remained the same as initial measurements. During the rice phase, bund height (APSIM resettable parameter max-pond) was set to 15 cm on the date it was established (prior to rice transplanting) and reset to zero on the date of rice field drainage via APSIM-Manager logic.

2.5.4.2. Crop rooting. Conservation agriculture practices encourage increased root length densities as well as deeper rooting (due to better soil structure) thus allowing water and nutrient uptake from deeper layers (Aggarwal et al., 1995; Sadras and Calvino, 2001; Qin et al., 2006). The root hospitality (kl in APSIM) and relative rate of root advance (xf in APSIM) were modified to capture CA performance. These values were adjusted iteratively (up to 20% increase) to produce a close match between the observed and simulated soil water extraction patterns. The temporal progression of the roots (xf) was not modified across CA treatments, nor was the root hospitality factor (kl). The changes to these factors between CA and CT systems were made to all the *Rabi* (winter) crops.

2.5.4.3. Soil microorganism activity. Soil microorganism activity in CA is assumed to be higher than in CT in the upper soil layers due to improved soil structure (Choudhary et al., 2018). This was captured in APSIM by increasing F_{biom} (fraction of soil organic matter present as microbial biomass) and decreasing F_{inert} (the inert fraction of soil organic matter) values in the upper two soil layers. The values of F_{biom} and F_{inert} were calibrated for CT and CA using data from zero-N treatments (CS2N1 to represent CT, and CS3N1 to represent CA). The source of mineral N in the zero-N treatments was assumed to come slightly from rainfall and/or irrigation water, and considerably from mineralisation of soil organic matter (Gaydon et al., 2017). These values (F_{biom} and F_{inert}) were varied within reasonable bounds (Probert et al., 1998) (around 20% change) to produce a good match between the observed and simulated crop yields in these zero-N treatments.

2.6. APSIM validation

The well parameterised and calibrated (using first year's data from selected treatments) APSIM model was validated against the experimental datasets from the rest of the treatments of the first year and all treatments of the second year to check the veracity of the model's calibration. Simulated model outputs were compared with the observed data set for all the three crops (rice, wheat, and mungbean) for a range of output variables including crop phenology dates, accumulated biomass over time, grain yield, soil NO_3^--N dynamics in top two soil layers (0–15 cm and 15–30 cm), and soil water content in two soil layers (15–30 cm and 60–75 cm).

2.7. Statistical tests used

The coefficient of determination (r^2), slope (α), and intercept (β) values from the linear regression of observed versus simulated data (1:1 graph) were used for the evaluation of the calibrated model. The model performance was also assessed using the Student's *t*-test of means assuming unequal variance P(*t*), and by comparing the absolute root means square error (RMSE, Eq. (1)) and normalised root means square error ($RMSE_n$, Eq. (2)) between simulated and observed values with the observed experimental variability.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(S_i - O_i)^2}{n}} \tag{1}$$

$$RMSE_n \quad (\%) = \left(\frac{\text{Absolute RMSE}}{\text{Mean of the observed}}\right) \times 100 \tag{2}$$

Where S_i is simulated, O_i is observed value, n is the number of pairs.

When the RMSE values are smaller or around the same quantum as the average standard deviation of the observed values, P(*t*) is larger than 0.05, together with high r^2 values, it indicates acceptable agreement between the observed and simulated outputs. Effectively, this demonstrates that the model is simulating system performance within the bounds of experimental uncertainty, and this is all you can expect a model to do (Gaydon et al., 2017).

3. Results

Observed crop performance (as well as the observed dynamics of soil and water, and irrigation requirement) varied between CT and CA practices across the two sites. This was detailed in Chaki et al. (2021a, 2021b) but is summarised here in Fig. S1 which illustrates this non 1:1 correlation relationship for a range of variables. This clearly indicates a performance difference between the two systems which models like APSIM must be capable of simulating. Results for relevant modelled aspects are detailed below.

3.1. Crop phenology

The model was calibrated for the fully fertilized and irrigated system (CS3N3), and then validated using the remainder of treatments. Fig. 2 illustrates the performance of APSIM in simulating crop phenological development in the rice-wheat-mungbean system (CA and CT cropping systems, each with three N levels are shown as an example). The crop phenology was successfully calibrated and validated under diverse tillage, irrigation, and N management (Figs. 2 and S4 shown as an example).

3.1.1. Rice phenological responses to N-stress

There was a good agreement between observed and simulated phenological stages of rice for the fully fertilised (full N) treatments. However, discrepancies were noted in capturing the rice phenological stages under N-stress treatments. We, therefore, set the phenological parameters independently for each different N-stress treatment to better capture the observed phenological stages of rice under that N-stress treatment (Figs. 2 and S4) as suggested by Gaydon et al. (2017).

3.1.2. Capturing phenology of observed crop failure in rainfed rice

APSIM-Oryza successfully simulated the phenology of observed crop failure (as the crop was highly water-stressed for a prolonged period, and high percolation rate in absence of puddling) in the second rice season in UPTR rice (CS6, rainfed) at Dinajpur (Fig. S4d–f). The model was able to capture the crop failure by increasing the simulated soil-water tension (water-stress factor WSTRESS in APSIM-Oryza, 1 means no stress, and 0 means maximum water-stress), which ceased the crop growth at the flowering stage and eventually crop death. The model was equally good for simulating rice phenological stages of the rainfed UPTR rice when the crop was moderately water-stressed (first season at Dinajpur) or non-water stressed (both seasons at Rajshahi) (Fig. S4a–f). This indicates APSIM-Oryza can capture the rice phenology in association with biomass accumulation (including crop death, details in Section 3.2.1) under a wide range of water-stress environments.

3.2. Grain and biomass yields of crops grown in a sequence without resets

The observed and simulated yields for crops were compared as a time series for all the treatments imposed in the trials. Figs. 3A and S5 illustrate the performance of APSIM in simulating crop production in the rice-wheat-mungbean system (CA and CT cropping systems, each with three N levels are shown as an example). Figs. 3A and S5 demonstrate a good model response in capturing diverse cropping systems with variable N rates, tillage, and residue decomposition without resetting system variables between crops.

3.2.1. Capturing crop failure (failed to produce grain, stunted biomass growth) in rainfed rice

APSIM-Oryza successfully simulated the observed crop failure to produce grain yield and stunted biomass growth in the second rice season in UPTR rice (rainfed- water-stressed) at Dinajpur (Fig. 3B(d–f)), as it captured the phenology of this water-stressed treatment. The model also performed well in simulating the above-ground biomass and grain yield of the rainfed rice under moderately water-stressed or non-water stressed conditions (Fig. S4B(a–f)).

3.2.2. Irrigation effects in wheat at shallow water table environment (Rajshahi)

The wheat crop did not suffer from water deficit stress under any irrigation treatments (fully irrigated to rainfed) at the shallow water table site (Rajshahi). Therefore, there was no observed yield (grain and biomass) difference among the imposed irrigation treatments in both wheat seasons (Chaki, 2021). APSIM-Wheat simulated the above-ground biomass and grain yield close to the observed values in each of the irrigation treatments (fully irrigated Fig. 3A and rainfed treatments Fig. 3B(a–c) shown as an example). The simulated crop utilised water from the shallow water table, consistent with observations.

3.2.3. Irrigation effects in wheat at deep-water table environment (Dinajpur)

The grain and biomass yield of wheat responded significantly under imposed irrigation treatments at the deep-water table site (Dinajpur) (Chaki, 2021). There was a good agreement between the simulated and observed above-ground biomass and grain yield for all imposed irrigation treatments (fully irrigated Fig. S5(a–f) and rainfed treatments Fig. 3B(d–f) shown as an example).

3.3. Soil NO_3^--N

The simulated changes in soil NO_3^--N over time for the fully fertilised (full N) and fully irrigated (CS1 to CS3) treatments are illustrated in Fig. 4 (Rajshahi site) and Fig. S6 (Dinajpur site). During the ponded rice phase, the soil NO_3^--N was close to zero, and then the soil NO_3^--N started to build up at the beginning of the upland wheat phase each year. The model was capable of simulating the soil NO_3^--N close to the boundary of experimental uncertainty among the replicates across the sites without resetting any system variables. In general, the model captured the dynamics of soil NO_3^--N better in the 15–30 cm soil layer than the 0–15 cm soil layer across the treatments and sites (Figs. 4 and S6). There was greater variability in the measured soil NO_3^--N data among the replicates at 0–15 cm soil layer (pooled standard deviation was 10.3 kg ha^{-1}) compared to the 15–30 cm soil layer (pooled standard deviation was 6.45 kg ha^{-1}). This might be due to the complex mechanism of distribution of NO_3^--N in topsoil layer (influenced much due to top dressing of N fertiliser) and thus shortcomings in sampling strategy for soil NO_3^--N (Probert et al., 1998).

3.4. Soil water dynamics

At Rajshahi, the soil water was measured using data-logging equipment in the first season and following the gravimetric method in the second season during the wheat phase only. Due to the presence of a shallow perched water table (Fig. S3), the wheat crop was not water-stressed under any irrigation treatment imposed (Chaki, 2021). The SOILWAT2 module in APSIM captured the soil water dynamics throughout the soil profile (compared at 15–30 cm and 60–75 cm soil depths) (Figs. 5A and S7A) in this shallow water table environment and associated crop production (grain and biomass yields) across the irrigation treatments (Table 2). The RMSE values ranged from 0.010 to 0.015 cm^3 cm^{-3} and RMSEn was $\leq$ 5% at 15–30 cm, the RMSE values ranged from 0.014 to 0.019 cm^3 cm^{-3} and RMSEn was $\leq$ 5% at 60–75 cm soil layer across the irrigation treatments (Table S1).

At Dinajpur, the soil water was measured daily using data-logging equipment throughout the experimental period which provides an opportunity to compare a large number of data points ($n = 760$). The crops (rice and wheat) responded to the irrigation treatments in terms of reduced grain and biomass production with the increment of water stress in wheat, and even a crop failure in the second season in rainfed rice. There was a wide diversity in the observed soil water datasets (across the treatments) including saturated to very dry soil conditions. The SOILWAT2 module in APSIM was capable of simulating these dynamic soil water changes over time adequately, including capturing the rewetting of the soil profile for irrigation and rainfall events and the subsequent drying of the soil (quite visible in the graphs). The crop response (in terms of grain and biomass production) to plant available water content was also captured well in the APSIM simulation, illustrated by high correlation (R^2), low bias (α, β), no significant difference between observed and simulated populations (as per student's T-test) and the RMSE being of similar quantum as the observed standard deviation (Tables 2, 4). The model simulated the changes in soil water content reasonably for the fully irrigated to deficit irrigated treatments

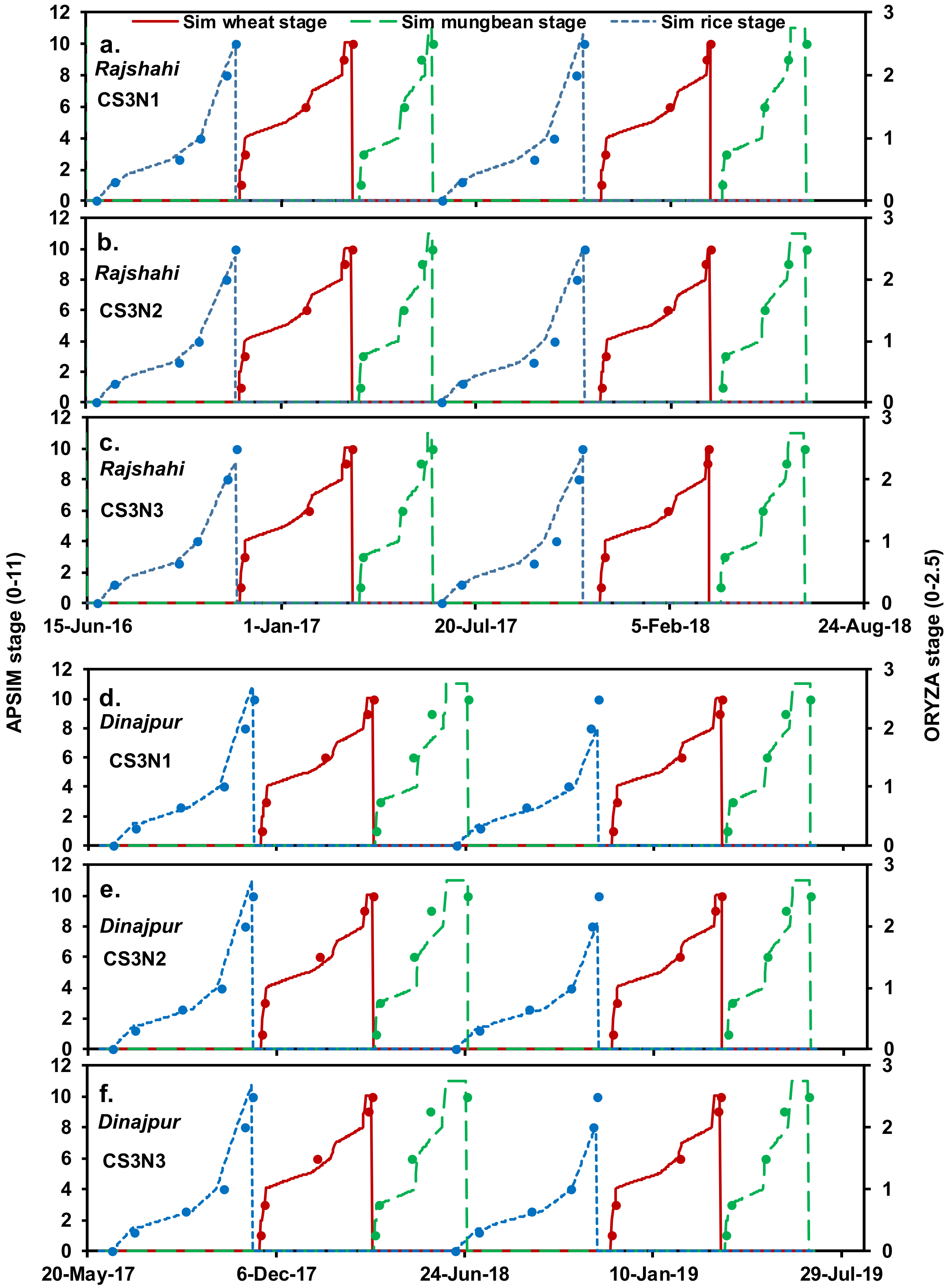

Fig. 2. Performance of APSIM in simulating crop phenological development in the rice-wheat-mungbean system. Simulated data are shown as continuous lines, measured data as discrete points. The wheat and mungbean crops refer to Y1 axis (APSIM crop stage – 0–11), with the rice crop on the Y2 axis (ORYZA crop stage – 0–2.5). The Y axis number refers to crop growth stages, with “0” being sowing, “11″ and “2.5″ being harvest for wheat/mungbean and rice, respectively. Graph (a to c) refer to CS3 system at Rajshahi; and (d to f) CS3 system at Dinajpur with three N rate (0, half and full of recommended N).

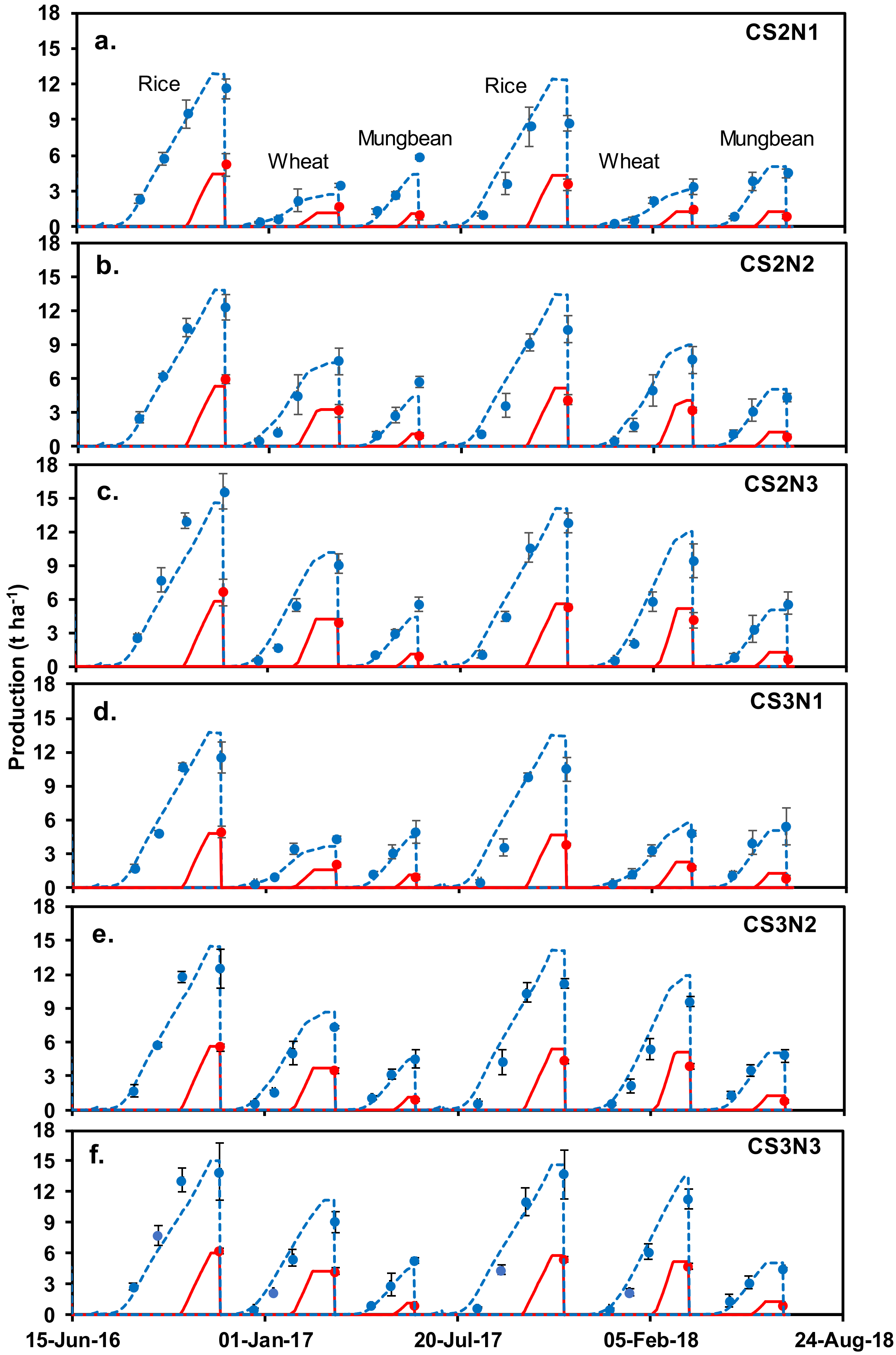

Fig. 3A. RAJSHAHI: Performance of APSIM in simulating crop production in the rice-wheat-mungbean system. Simulated data are shown as continuous lines (solid line- grain yield; broken line- above-ground biomass), measured data as discrete points (blue - biomass; red - grain yield) with associated error bars (one standard deviation either side of the mean). Graph (a to c) refer to CT system; and (d to f) CA system with three N rate (0, half and full of recommended N).

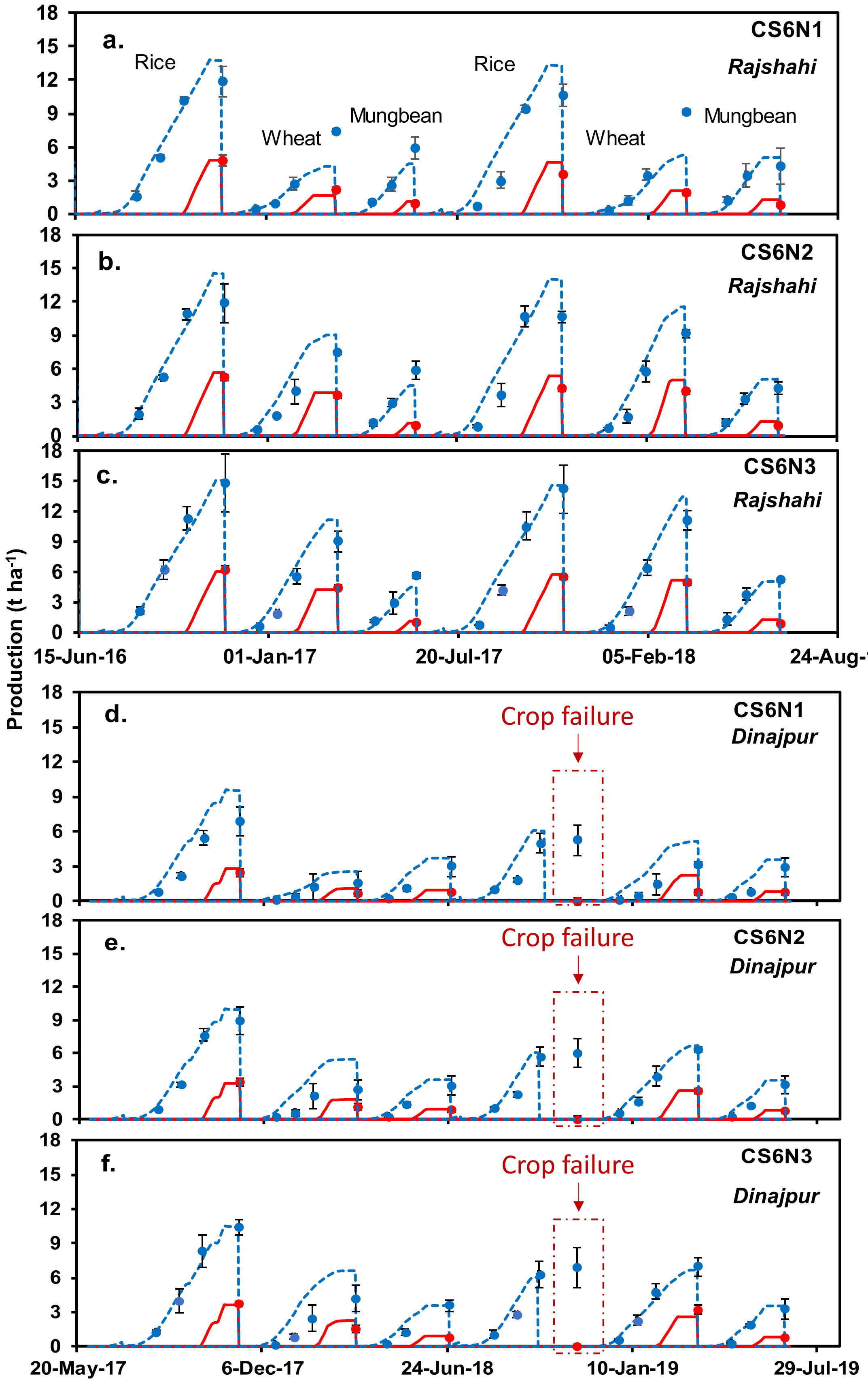

Fig. 3B. Performance of APSIM in simulating crop production in the rice-wheat-mungbean system in rainfed environment. Simulated data are shown as continuous lines (solid line- grain yield; broken line- above-ground biomass), measured data as discrete points (blue - biomass; red - grain yield) with associated error bars (one standard deviation either side of the mean). Graph (a to c) refer to CS6 system at Rajshahi; and (d to f) CS6 system at Dinajpur with three N rate (0, half and full of recommended N). The stunted crop development in the second season rice crop (c to d) at Dinajpur is an observed crop failure, which APSIM successfully simulated.

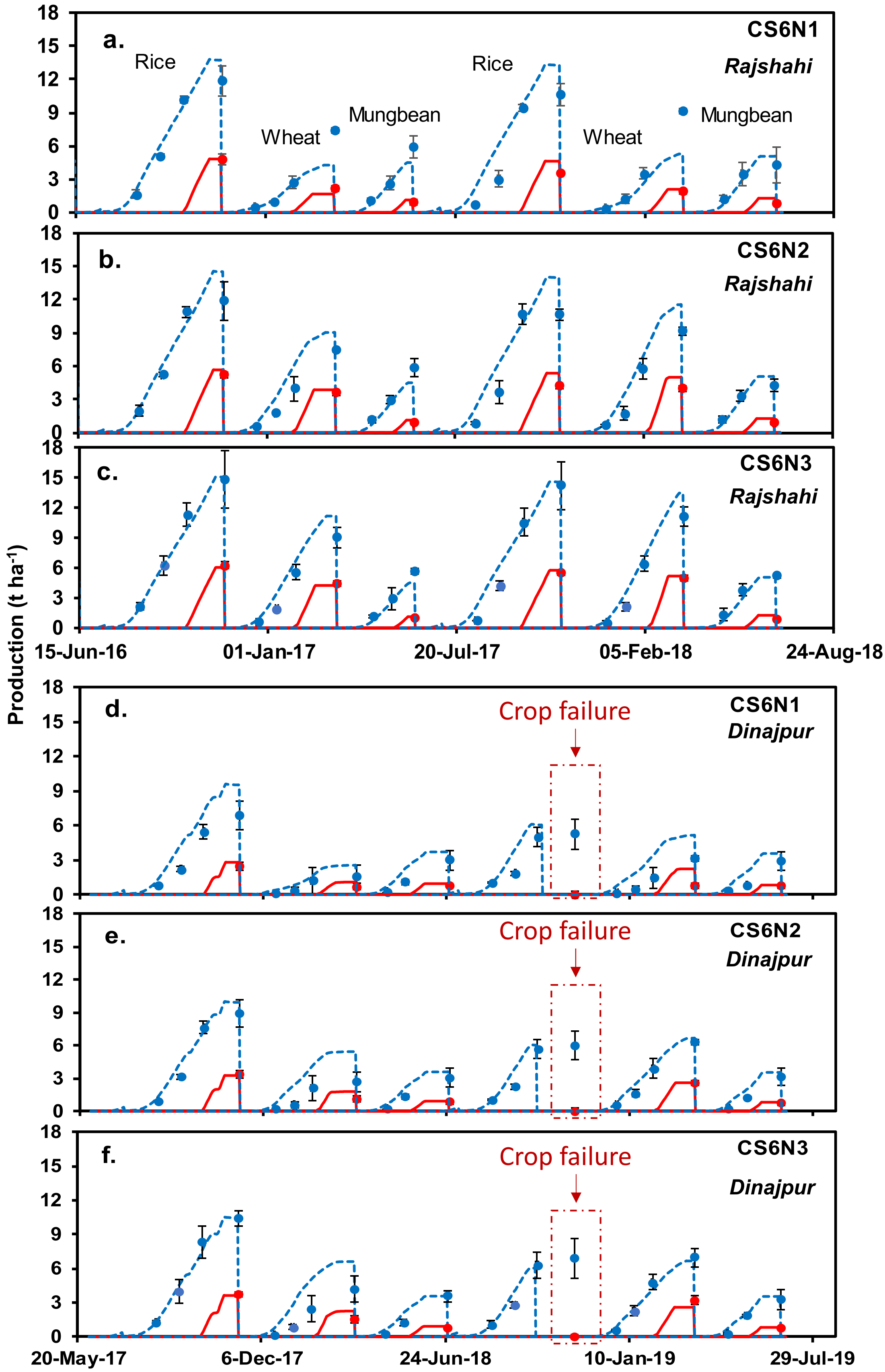

Fig. 4. RAJSHAHI: Comparison between measured and simulated soil NO_3^--N in top two soil layers (0–15 cm and 15–30 cm) during the wheat growing season in 2016–17 and 2017–18 in fully fertilized and irrigated cropping systems (CS1 = PTR Rice – CT Wheat, CS2 = PTR Rice – CT Wheat – CT Mungbean and CS3 = UPTR Rice – ZT Wheat – ZT Mungbean). Simulated data are shown as solid lines, measured data as discrete points with associated error bars (one standard deviation either side of the mean).

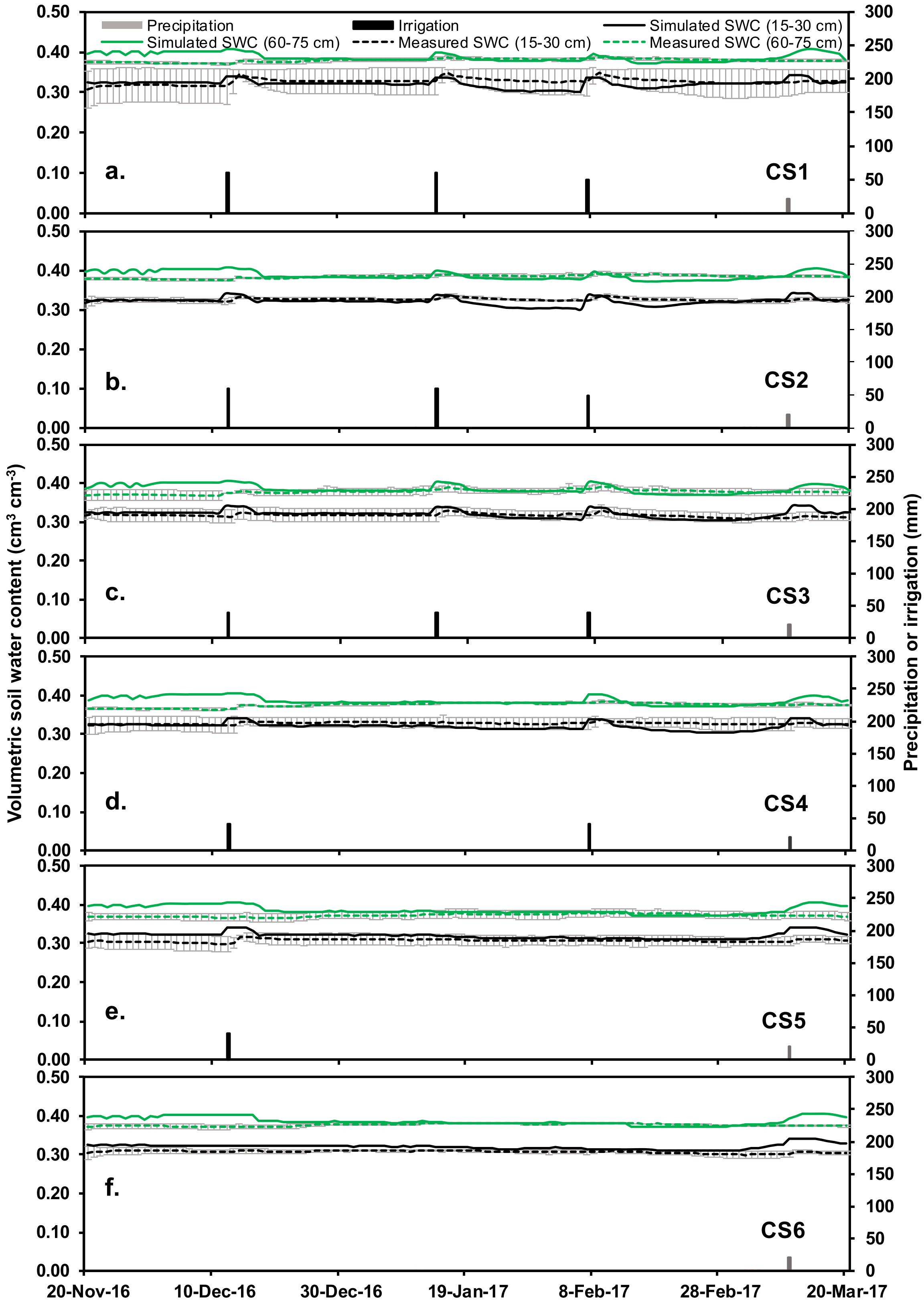

Fig. 5A. RAJSHAHI: Comparison between measured and simulated soil water content (cm^3 cm^{-3}) in two soil layers (15–30 cm and 60–75 cm) during the wheat growing season in 2016–17 across the fully fertilized cropping system treatments evaluated in the field experiment (CS1 = PTR Rice – CT Wheat, CS2 = PTR Rice – CT Wheat – CT Mungbean, CS3 = UPTR Rice – ZT Wheat (3 irrig.) – ZT Mungbean, CS4 = UPTR Rice – ZT Wheat (2 irrig.) – ZT Mungbean, CS5 = UPTR Rice – ZT Wheat (1 irrig.) – ZT Mungbean and CS6 = UPTR rainfed Rice – ZT Wheat (0 irrig.) – ZT rainfed Mungbean). Simulated data are shown as solid lines, measured data as broken lines with associated error bars (one standard deviation either side of the mean).

Table 2
Statistical analysis of APSIM performance for observed versus simulated grain and biomass yields across the treatments evaluated in the field experiments.

Variable	n	X_{sim}	X_{obs} (SD)	P (t *)	α	β	R^2	RMSE	$RMSE_n$ (%)
Rajshahi									
Calibration									
Grain	10	3121	3241 (419)	0.90	0.95	52	0.98	336	10
Biomass	55	4892	4758 (571)	0.86	0.99	196	0.91	1261	27
Validation									
Grain	92	3490	3133 (339)	0.19	0.98	406	0.94	590	19
Biomass	323	5393	4844 (718)	0.09	1.06	274	0.92	1375	28
Dinajpur									
Calibration									
Grain	10	2585	2693 (264)	0.89	0.98	-65	0.90	554	21
Biomass	55	4323	4091 (656)	0.76	0.90	638	0.89	1335	33
Validation									
Grain	92	2675	2524 (276)	0.56	1.02	94	0.95	438	17
Biomass	323	4097	3779 (666)	0.26	0.96	460	0.89	1257	33

n, number of data pairs; Xsim, mean of simulated values; Xobs, mean of observed values; SD, standard deviation; P(t *), significance of Student's paired *t*-test assuming non-equal variances; α, slope of linear regression between simulated and observed values; β, y-intercept of linear regression between simulated and observed values; RMSE, absolute root mean squared error; RMSEn, normalized root mean squared error.

Table 3
Statistical analysis of APSIM performance for observed versus simulated yield at zero N rate across the cropping system treatments evaluated in the field experiments.

Variable	n	X_{sim}	X_{obs} (SD)	P (t *)	α	β	R^2	RMSE	$RMSE_n$ (%)
Rajshahi									
Grain									
CS1	4	2775	2714 (331)	0.96	1.10	-211	0.89	559	21
CS2	6	2258	2220 (370)	0.97	0.88	295	0.89	526	24
CS3	6	2612	2379 (239)	0.81	0.98	274	0.93	470	20
CS4	6	2622	2366 (399)	0.79	1.03	181	0.94	469	20
CS5	6	2610	2412 (308)	0.83	1.03	119	0.86	604	25
CS6	6	2590	2350 (337)	0.80	1.03	162	0.91	517	22
Biomass									
CS1	16	4468	3965 (657)	0.72	1.17	-168	0.90	1567	40
CS2	22	4003	3765 (486)	0.82	1.11	-184	0.92	1131	30
CS3	22	4438	4179 (509)	0.82	1.10	-149	0.92	1183	28
CS4	22	4452	4009 (693)	0.69	1.13	-95	0.86	1602	40
CS5	22	4449	4113 (763)	0.76	1.15	-288	0.89	1418	34
CS6	22	4439	4070 (635)	0.74	1.13	-143	0.89	1410	35
Dinajpur									
Grain									
CS1	4	2551	2875 (337)	0.83	1.25	-1054	0.92	730	25
CS2	6	1976	2161 (267)	0.86	1.07	-340	0.89	621	29
CS3	6	2080	1918 (322)	0.85	1.31	-424	0.94	520	27
CS4	6	2073	1851 (311)	0.81	1.14	-45	0.99	310	17
CS5	6	2091	1859 (338)	0.80	1.07	109	0.99	274	15
CS6	6	1306	917 (191)	0.48	1.05	346	0.73	615	67
Biomass									
CS1	16	3531	4354 (687)	0.56	1.02	-891	0.86	1706	39
CS2	22	3173	3597 (444)	0.69	0.94	-206	0.83	1518	42
CS3	22	3479	2685 (576)	0.40	1.33	-84	0.92	1510	56
CS4	22	3448	2488 (521)	0.30	1.44	-126	0.96	1562	63
CS5	22	3463	2678 (715)	0.41	1.31	-32	0.96	1297	48
CS6	22	3126	2462 (511)	0.34	1.08	470	0.88	1068	43

n, number of data pairs; Xsim, mean of simulated values; Xobs, mean of observed values; SD, standard deviation; P(t *), significance of Student's paired *t*-test assuming non-equal variances; α, slope of linear regression between simulated and observed values; β, y-intercept of linear regression between simulated and observed values; RMSE, absolute root mean squared error; RMSEn, normalized root mean squared error.

(CS1 to CS5), however, slightly underestimated the soil water content in the upper soil layer (15–30 cm depth) and slightly overestimated in the deeper soil layer (60–75 cm depth) (Figs. 5B and S7B). The RMSE values ranged from 0.027 to 0.036 $cm^3\ cm^{-3}$ and RMSEn was ≤ 15% across the soil depths and deficit irrigation treatments (CS1 to CS5), the RMSE values for the rainfed treatment (CS6) ranged from 0.041 to 0.044 $cm^3\ cm^{-3}$ and RMSEn was 17–19% across the soil depths (Table S1).

The simulated soil water content at 0–15 cm soil depth was influenced by differences in the surface residue retained between the two systems (CT and CA) which was reflected in our analysis (Fig. S8; non 1:1 trendline slope).

3.5. Performance across all treatments

The model performance was evaluated by plotting observed versus simulated grain and biomass yield. The overall model performance in capturing the systems dynamic of nitrogen, tillage, residue decomposition, and water without resetting system variables indicate good model calibration and validation. Fig. 6 shows the comparison of observed versus simulated grain and biomass yield (Fig. 6a, c) for the calibration and (Fig. 6b, d) for the validation datasets across all the treatments, and Table 2 shows associated statistics. The RMSE of 336 kg ha^{-1} at Rajshahi and 554 kg ha^{-1} at Dinajpur for the grain yield of the calibration dataset are close to the observed standard deviation among the experimental replicates (419 kg ha^{-1} at Rajshahi and 264 kg ha^{-1} at

Table 4
Statistical analysis of APSIM performance for observed versus simulated yield at full N rate across the cropping system treatments evaluated in the field experiments.

Variable	n	X_{sim}	X_{obs} (SD)	P (t *)	α	β	R^2	RMSE	$RMSE_n$ (%)
Rajshahi									
Grain									
CS1	4	5218	4825 (448)	0.56	0.60	2325	0.74	615	13
CS2	6	3866	3613 (307)	0.85	0.87	708	0.94	614	17
CS3	6	3933	3737 (452)	0.88	0.96	340	0.99	303	8
CS4	6	3932	3780 (309)	0.91	0.92	437	0.98	383	10
CS5	6	3932	3694 (537)	0.86	0.93	502	0.98	408	11
CS6	6	3933	3824 (331)	0.94	0.94	318	0.99	265	7
Biomass									
CS1	16	6872	5931 (657)	0.55	1.02	802	0.94	1459	25
CS2	22	5752	5568 (665)	0.89	0.93	597	0.91	1328	24
CS3	22	5941	5607 (750)	0.81	0.98	450	0.92	1331	24
CS4	22	5940	5635 (845)	0.83	0.97	486	0.91	1420	25
CS5	22	5937	5316 (859)	0.65	1.03	460	0.94	1275	24
CS6	22	5936	5535 (855)	0.77	1.01	360	0.95	1128	20
Dinajpur									
Grain									
CS1	4	4785	4559 (353)	0.79	0.80	1128	0.76	555	12
CS2	6	3513	3308 (322)	0.87	1.02	146	0.96	451	14
CS3	6	3540	3212 (301)	0.79	1.02	272	0.95	553	17
CS4	6	3330	3118 (258)	0.86	1.02	159	0.92	561	18
CS5	6	3067	3031 (284)	0.98	1.06	-142	0.97	344	11
CS6	6	1694	1670 (195)	0.98	0.88	221	0.93	371	22
Biomass									
CS1	16	5884	6156 (1000)	0.87	0.81	867	0.88	1723	28
CS2	22	4862	5062 (784)	0.88	0.83	670	0.91	1451	29
CS3	22	5001	4316 (684)	0.59	1.02	602	0.96	1106	26
CS4	22	4805	4134 (738)	0.58	1.01	634	0.94	1167	28
CS5	22	4628	4033 (737)	0.60	1.00	596	0.94	1126	28
CS6	22	3746	3669 (788)	0.93	0.81	759	0.86	1117	30

n, number of data pairs; Xsim, mean of simulated values; Xobs, mean of observed values; SD, standard deviation; P(t *), significance of Student's paired *t*-test assuming non-equal variances; α, slope of linear regression between simulated and observed values; β, y-intercept of linear regression between simulated and observed values; RMSE, absolute root mean squared error; RMSEn, normalized root mean squared error.

Dinajpur). The overall R^2 value for grain yield of the calibration dataset is 0.98, with low bias (α = 0.95, β = 52) at Rajshahi and R^2 value of 0.90, with low bias (α = 0.98, β = −65) at Dinajpur indicating acceptable model calibration. The RMSE of 590 kg ha^{-1} at Rajshahi and 438 kg ha^{-1} at Dinajpur for the grain yield of the calibration dataset are close to the observed standard deviation among the experimental replicates (339 kg ha^{-1} at Rajshahi and 276 kg ha^{-1} at Dinajpur). The overall R^2 value for grain yield of the validation dataset across the treatments is 0.98, with low bias (α = 0.98, β = 406) at Rajshahi and an R^2 value of 0.95, with low bias (α = 1.02, β = 94) at Dinajpur indicating strong evidence for successful model validation over the variety of datasets (n = 92 at each site) tested. The performance of APSIM calibration and validation for biomass yield over a wide range of datasets (n = 55 for calibration, and n = 323 for validation at each site) also indicate acceptable model performance (Fig. 6 and Table 2).

The performance of APSIM in simulating crop production with zero N fertiliser applied (nutrition solely from indigenous soil N sources) and full N rate across the cropping systems with associated statistics are given in Tables 3 and 4. The overall high correlation (R^2), low bias (α, β), no significant difference between observed and simulated populations with all values greater than 0.05 according to student's T-test and the RMSE being of similar quantum as the observed standard deviation, indicates acceptable model performance.

4. Discussion

4.1. Model performance

The APSIM model was evaluated over a range of cropping system management interventions in the rice-wheat system, including CA vs CT, irrigation, N rate, residue allocation for two diverse environments (differing in soil types, water table dynamics, and agro-climate) in the EGP of South Asia. The study was conducted without resetting any APSIM state variables each year, and this is important because it demonstrates that the dynamics of system processes are being well-simulated (Gaydon et al., 2017). The performance of APSIM in simulating both the above-ground (e.g., crop phenology, crop production) and below-ground processes (e.g., soil water dynamics, soil NO_3^--N dynamics) was reasonably good across the cropping system treatments over the sites.

4.1.1. Crop phenology

The model's ability to correctly simulate the crop phenological development stages largely determine the simulated crop production, and therefore treated as the first aspect of model calibration (Gaydon et al., 2018). The simulated crop phenology dates of wheat and mungbean were close to those observed across the treatments (under varied N rates, and irrigation management), confirming that APSIM crop modules sensibly consider the accumulation of thermal time (cumulative degree days) to move from one crop developmental phase to the next phase. However, due to the inability of APSIM-Oryza to capture the phenology response of rice crops to soil N variation (Bouman and Van Laar, 2006; Gaydon et al., 2017), we created three 'rice varieties' in APSIM for each N rate treatment (zero, half, and full N rate) as it was worked-around with modified crop phenology parameters by Gaydon et al. (2017) to overcome this issue. The N-stress rice phenology issue is not a big deal because normally the crop will have recommended N applied and will be unstressed. It only mattered for our calibration-validation exercise when we purposely N-stressed the crops.

4.1.2. Grain and biomass yield of crops grown in a sequence without resets

Simulation of crop production (grain and biomass) under diverse cropping system interventions (with variable N rates, tillage, residue allocation, irrigation management, soil types, and water table dynamics), and without resetting system variables indicated the strong capability of APSIM in simulating crop response to those factors. The

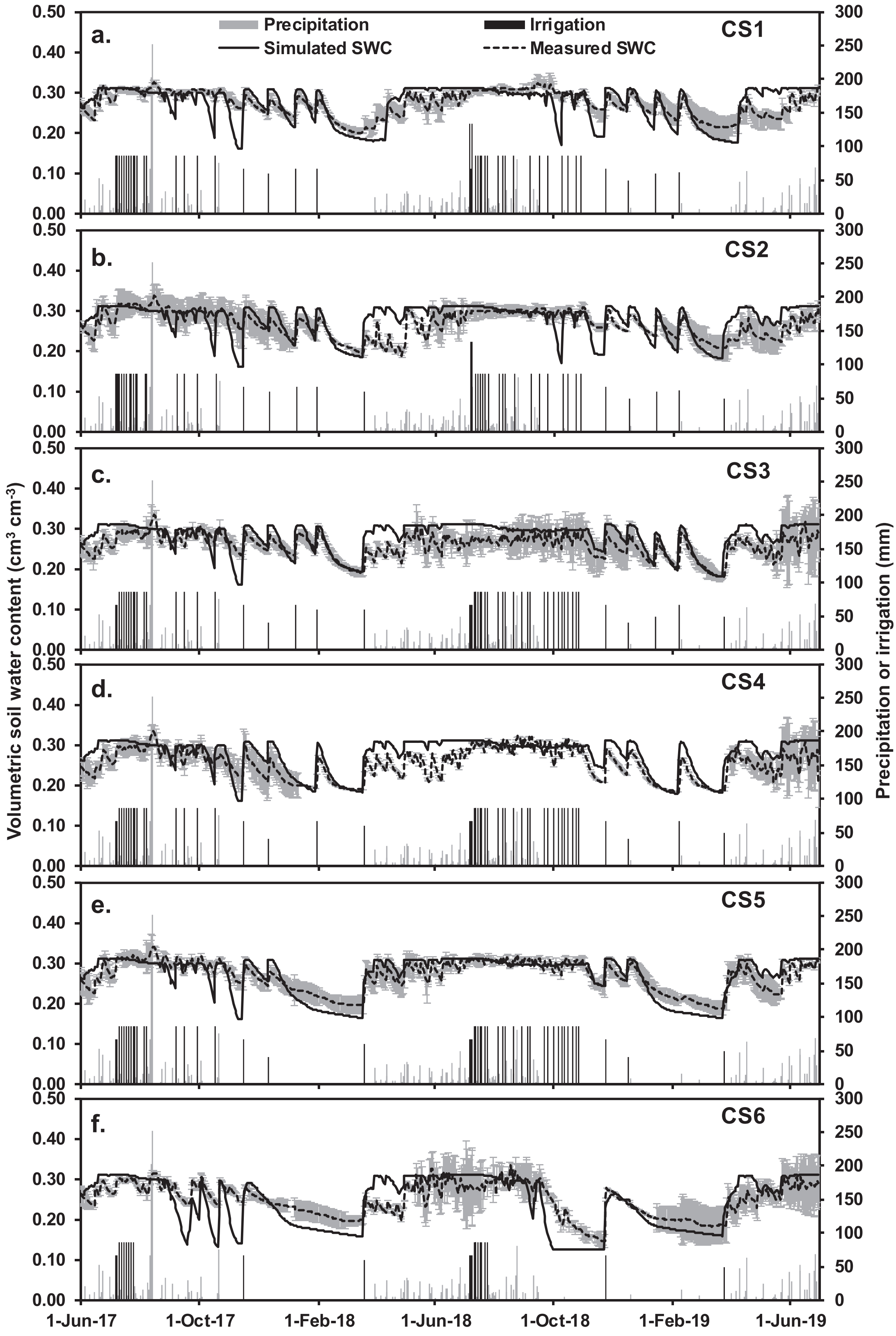

Fig. 5B. DINAJPUR: Comparison between measured and simulated soil water content (cm^3 cm^{-3}) in 15–30 cm soil layer during 2017–19 across the fully fertilized cropping system treatments evaluated in the field experiment (CS1 = PTR Rice – CT Wheat, CS2 = PTR Rice – CT Wheat – CT Mungbean, CS3 = UPTR Rice – ZT Wheat (3 irrig.) – ZT Mungbean, CS4 = UPTR Rice – ZT Wheat (2 irrig.) – ZT Mungbean, CS5 = UPTR Rice – ZT Wheat (1 irrig.) – ZT Mungbean and CS6 = UPTR rainfed Rice – ZT Wheat (0 irrig.) – ZT rainfed Mungbean). Simulated data are shown as solid lines, measured data as broken lines with associated error bars (one standard deviation either side of the mean).

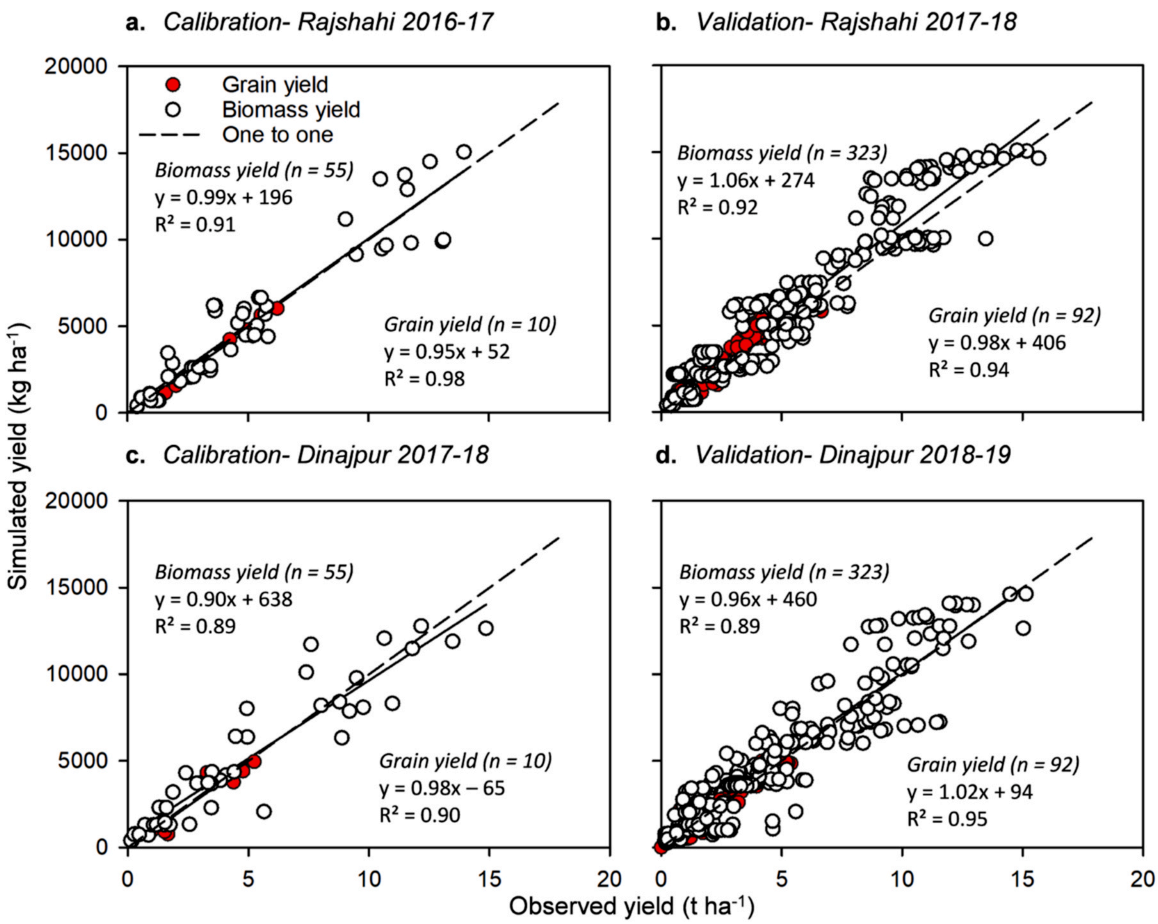

Fig. 6. Comparison between observed and simulated grain and biomass yield of rice, wheat and mungbean crop across all the cropping system and N rate treatments evaluated in the field experiments at Rajshahi and Dinajpur.

performance of the APSIM model was markedly better in the full-N than in zero-N rate, but both are still considered acceptable. There was a tendency to over simulate biomass production in the zero N, particularly in the first season. This improved in the second season, indicating that the model was overcoming uncertainties in initial mineral soil N and moisture conditions, and reducing model error. This gives confidence in using the model for longer-term simulations.

During the rice phase, there was an observed crop failure in rainfed rice in the second year at the sandy loam site (Dinajpur). The rice crop in this treatment (CS6) was highly water-stressed for a prolonged period which caused ceasing of crop growth at the flowering stage leading to no grain production (Chaki et al., 2021b), consistent with the findings of other researchers who reported rice crop failure due to drought stress in Asia (Naklang et al., 1996; Fukai, 1999). The APSIM-Oryza captured the crop failure very accurately which indicates the model's ability to capture crop response under a wide range of water stress environments. Li et al. (2015) also used ORYZA2000 (which plugged in to the APSIM model) successfully in simulating drought stress impacts (including crop failure) of climate change on rainfed rice in South Asia.

During the wheat phase, there was no yield response to irrigation treatments at the shallow water table site (Rajshahi), whereas, the wheat grain yield decreased consistently with increasing water stress at the deep-water table site (Dinajpur). The reason was that the wheat crop was not water-stressed as the wheat roots most likely utilised water from the shallow water table at the Rajshahi site, and the observed yield reduction at the Dinajpur site was due to the reduction of spike density and grain number in the lower water regime (Chaki, 2021). The model captured the response of the wheat crop to irrigation treatments by simulating the crop yield consistently as observed under these diverse water table environments. This demonstrated reliable performance of APSIM, and therefore could be used in assessing the impacts of irrigation scheduling options in wheat in a range of environments.

Simulating production (grain and biomass) under CA and CT management in the rice-wheat system without annual resetting of soil parameters (soil, water, nutrients) at the diverse sites indicated the strong capacity of APSIM to simulate system processes in the CA and CT practices. Balwinder-Singh et al. (2015) also successfully simulated (using APSIM) the CA and CT practices in the irrigated and fully fertilised rice-wheat system for the first time in the NW-IGP. However, our evaluation of APSIM under CA and CT practices considering a range of irrigation, residue, and N management at diverse sites is the unique attempt of using the cropping system simulation model in the EGP. The evaluation was robust as the model captured the differences between CA and CT management, and its ability to simulate reasonable response for the treatments applied in the two contrasting environments.

4.1.3. Soil NO_3^--N

When a model simulates the below-ground processes (e.g., soil N dynamics, soil water) adequately in association with above-ground processes (e.g., crop production), we can say that the model could be widely applicable for investigating cropping systems options from different aspects. The performance of SOILN module in predicting the changes in soil NO_3^--N was generally good, given that there were large uncertainties in measuring the soil NO_3^--N (Figs. 4 and S6). The ability of SOILN in capturing the N mineralisation, crop N uptake under a range of manure and fertiliser application was also confirmed by laboratory incubation and field studies conducted in India (Mohanty et al., 2011, 2012).

4.1.4. Soil water dynamics

Simulating soil water is the foremost variable (especially for water-limited environments) which should be simulated quite sensibly for the analysis of trade-offs of water allocation using the cropping systems model. The SOILWAT2 module did an excellent job of simulating the dynamics of soil water under shallow water table environments, and also performed sensibly for the fully irrigated to deficit irrigated treatments under deep-water table environments. The reason for the slight underestimation of soil water in the upper soil layer and slight overestimation in the deeper soil layer in the rainfed treatment (CS6) in deep-water table site (Dinajpur) is not fully understood. One reason might be due to the comparatively greater extraction of soil water from the upper soil layer, and less extraction from the deeper soil layer in the model than the actual crop water extraction from those soil layers. We tried to work out this by iteratively changing the root hospitality factor at different depths which improved the soil extraction pattern but might need more adjustment under high water-stressed conditions. Another possibility might be due to less accuracy in measuring soil water (using GS1 dielectric soil moisture sensor) in dry soil, possibly due to poor contact between soil and the soil moisture sensor from air interference. This possibility was confirmed by the fact that there were negative readings on a soil moisture sensor installed in the water-stressed treatments, therefore we discarded those exceptional values.

4.2. Model applicability, limitations, and scope of model improvement

The majority of the farmers in the EGP followed the traditional method for practicing the rice-wheat system which is resource inefficient, and less productive. Several recent studies conducted in the EGP region indicated that CA-based management interventions could make the rice-wheat system more productive and resource-efficient with less environmental impacts (Islam et al., 2019; Gathala et al., 2020; Chaki et al., 2021a), however, the magnitude of benefits varied across sites (soil types, climates, and landscapes) (Chaki et al., 2021a). Comparatively less attention has been given to the CA research in the EGP, and thus there is a deficiency of long-term data on CA in the literature which could give greater insights into the performance of CA interventions and underlying mechanisms in these environments.

Although CA vs CT systems have been simulated for irrigated rice-wheat systems in the NW-IGP (rarely), this is the first attempt in the EGP, and it was found to be successful. We have demonstrated that when certain principles about changing soil properties (e.g., Ks, BD) and crop rooting parameters (e.g., xf, kl in APSIM) between CA and CT are followed then APSIM simulates the performance of these crop management practices well. The model's ability to differentiate CA vs CT management at diverse sites (varied soil types, water table dynamics, and agro-climates) under a range of irrigation (fully irrigated to rainfed), N management (fully fertilised to unfertilised), and residue management (partial residue retention to no-retention) by simulating system dynamics (e.g., system production, water, and N dynamics) without annual resets of model parameters (e.g., water, nutrients, soil) demonstrated APSIM's capacity to reliably simulate the rice-wheat system under varied management conditions. Our evaluation of the APSIM model from a wide range of perspectives demonstrates robustness in how we have modified the key soil parameters (Ks, BD, kl, F_{biom}, F_{inert}) and gives confidence in using the model for future exploration of cropping system options and answering research questions related to CA management including better irrigation, N, residue managements, the suitability of CA in different environments, and impacts on soil and environmental factors.

During the calibration and validation process of the APSIM (v7.5) model, we have modified soil variables and crop rooting manually (associated with tillage, to better capture the CA and CT environments), and also used three independent 'rice variety' each for full N, moderate N and zero N rate (to better capture the N-stress effect on rice phenology). For the benefit of wider APSIM users, improvements of the model are needed which could do these modifications on soil properties changes automatically for the respective management practices (CA, and CT). The primary innovation presented in this paper is that crop performance differences between CA and CT practices can be simulated across diverse sites by modification of key APSIM soil parameters by generic factors. This suggests that these cropping system differences can reliably be simulated across soil and climatic gradients through the use of these factors.

5. Conclusions

Simulation models must be well tested before being employed in scenario analyses. The APSIM model was calibrated and validated under varied tillage, residue, N rates, and irrigation practices in diverse environmental conditions. The robustness of APSIM's capacity to simulate rice-wheat cropping system performance with no annual variable resets, offers great confidence that the model can realistically capture diverse management practices followed in rice-wheat systems in the EGP of South Asia. Our validation testing with highly variable datasets (e.g., zero-N to full-N, zero irrigation to full irrigation, zero tillage to full tillage, zero crop yield to potential yield) from diverse environments (soil types, water table dynamics, and agro-climatic conditions) has allowed us to identify where APSIM performs well (e.g., capturing crop failure, response to full-N, crop rotations, water dynamics) and some areas where improvements could be focussed (e.g., N-stress effect on rice phenology, modifications on soil properties changes automatically for CA and CT). These findings are relevant to the wider APSIM and general crop modelling community. But primarily our study has demonstrated that when different values for key model input parameters are employed in simulating the differences between CA and CT practices in rice-wheat cropping systems (i.e. an increase of Ks (100%), a decrease of BD (5%), an increase of the crop rooting parameters (xf, kl- up to 20% increase) and soil microorganism activity (increasing F_{biom} and decreasing F_{inert} - around 20% change) in CA compared with CT), APSIM performance in differentiating the outcomes from CA vs CT management across wet, fine-textured soil environments, and dry coarse-textured soil environments in the EGP is good. This positions APSIM strongly to conduct future scenario analyses comparing CA and CT systems across different soil and climate gradients. Our research is the first examination and clarification of this issue for rice-wheat cropping systems in the EGP. The validated APSIM framework is now deemed suitable for scenario analyses which may include exploring long-term variability in crop yield and soil organic C, better irrigation and N management, greenhouse gas emission implications, and the effects of climatic change.

Declaration of Competing Interest

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

Acknowledgements

The authors thank the Australian Centre for International Agricultural Research (ACIAR) for the financial support to the first author's Ph. D. research at the University of Queensland (UQ) through John Allwright Fellowship, and CSIRO, BARI, BWMRI, CIMMYT and UQ for supporting fieldwork in Bangladesh through ACIAR project CSE/2011/077 "Sustainable and resilient farming systems intensification in the Eastern Gangetic Plains (SRFSI)".

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.fcr.2021.108344.

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