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RESEARCH ARTICLE

Modelling rice performance in Telangana: CERES-rice calibration and validation for post-monsoon cultivar adaptation

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Abstract

Rice, the staple food for more than 60 % of the global population, faces increasing production challenges due to climate variability and resource constraints. Accurate crop growth modelling and yield prediction are therefore essential to strengthen food security and optimise management. This study aimed to calibrate and validate the CERES-rice model within the decision support system for agrotechnology transfer (DSSAT v4.8.5.0) for three cultivars, RNR-15048, KNM-1638 and JGL-24423, across multiple sowing dates under *Rabi* conditions in Telangana, India. Field experiments were conducted during the rabi seasons of 2023 and 2024 using a split-plot design with five sowing windows and three cultivars. Site-specific weather, soil, crop management and genotype datasets were compiled and genetic coefficients were estimated through iterative calibration. Model performance was evaluated using root mean square error (RMSE), normalised RMSE (nRMSE) and the index of agreement (d). Calibration results showed excellent accuracy, with phenology simulated within ±1 day (nRMSE 1.2–3.7 %; d >0.83) and grain yield deviations <2.5 % (nRMSE 3.4–3.6 %; d >0.85). Biomass and straw yields were reproduced with good agreement (nRMSE <10.5 %). Validation confirmed robust model performance, with phenology and grain yield consistently accurate across cultivars and biomass predictions genotype-dependent but acceptable. Straw yield was more variable, particularly for KNM-1638 (nRMSE 11.2 %), though overall trends were reliable. The calibrated genetic coefficients were physiologically realistic and consistent with Indica rice, confirming the model's suitability for yield forecasting, sowing window assessment and management optimisation under *Rabi* conditions. Overall, these findings highlight the potential of the CERES-rice model to support climate-smart rice production strategies in South Asia.

Keywords: DSSAT-CERES rice; genetic coefficients; phenology; rabi rice; Telangana; yield prediction

Introduction

Rice is the staple food for more than 60 % of the global population (1). With the rapidly increasing global population, ensuring a stable and adequate rice supply has become increasingly critical (2). However, in recent decades, yield gains have slowed due to resource and environmental constraints. Rice cultivation is increasingly challenged by high temperature, drought, rainfall, greenhouse gases, soil fertility and irrigation resources, factors that are further intensified by climate change (3). India, the second-largest producer of rice in the world, plays a vital role in global rice production. The rice crop is cultivated on 47.82 M ha, producing 137.82 MMT annually, with an average productivity of 2882 kg ha^{-1} (4). In Telangana, rice occupied 4.69 M ha, producing 16.87 million metric tons annually with a productivity of 3602 kg per hectare (4). Nevertheless, rice growth and yield remain strongly influenced by environmental variability, particularly temperature and rainfall, leading to considerable year-to-year fluctuations. Reliable and timely information on crop growth and yield at national, regional and global scales is therefore essential for food security planning (5). Accurate yield forecasting not only informs evidence-based policy but also equips farmers to reduce risks and optimise resources through improved management strategies.

Crop simulation models have emerged as powerful tools for integrating soil, weather, genetic and management factors to predict crop performance under diverse environments. Among them, the CERES-rice model, a component of the Decision Support System for Agrotechnology Transfer (DSSAT), has been extensively applied to simulate phenology, biomass accumulation, assimilate partitioning, grain yield and harvest index with high accuracy (6). Through its ability to capture genotype × environment × management (G × E × M) interactions, DSSAT supports the optimisation of production practices, risk management and climate change impact assessments (7, 8). Beyond field-level applications, DSSAT has been employed in crop forecasting, sustainable cropping system design and regional adaptation strategies (9, 10). Recent advancements further integrate DSSAT with climate models, GIS and remote sensing to strengthen drought management and regional yield estimation (11). Despite its wide application, limited studies are available on the calibration and validation of the CERES-rice model for post-monsoon rice in Telangana, particularly with respect to genotype-specific parameters and the different grain types of cultivars grown under varied environments. This gap underscores the necessity of cultivar-specific calibration to improve the understanding of model performance for post-monsoon rice cultivation, which experiences distinct climatic and photoperiodic conditions compared to the *kharif* season. Moreover, locally calibrated genetic coefficients for modern, high-yielding *Rabi* cultivars such as RNR 15048, KNM 1638 and JGL 24423 remain unavailable, limiting model accuracy and regional adaptability assessments. To ensure dependable predictions, accurate calibration and validation of crop models are essential. This requires high-quality field data on crop growth, nitrogen uptake, soil water balance and biomass partitioning, which enhances the precision of simulations (12). In this context, the present study was undertaken to calibrate and validate the CERES-rice model using field experiments across multiple sowing dates and rice cultivars. The specific objective of this study was to evaluate the performance of the CERES-rice model in simulating phenology, biomass accumulation and yield across varying sowing date scenarios.

Materials and Methods

The field study was conducted during two consecutive rabi seasons (2023 and 2024) at the Regional Sugarcane and Rice Research Station, Professor Jayashankar Telangana Agricultural University (PJTAU), Rudrur, Telangana (18°56′45″ N, 77°87′73″ E; 404 m amsl), Telangana and which lies within the Northern Telangana Agro-climatic Zone. During the 2023 rabi season, the mean daily maximum and minimum temperatures were 33.75 ° C and 20.57 °C, respectively. The average relative humidity (RH I) was 72.32 % and the relative humidity (RH II) averaged 40.15 %. The crop period received 168.49 mm of rainfall distributed over 7 days. In *Rabi* 2024, mean maximum and minimum temperatures were slightly lower at 33.64 °C and 18.03 °C. RH I averaged 68.2 % and RH II 40.28 %. Seasonal rainfall amounted to 257.2 mm over 10 rainy days. The experimental field was sandy clay loam and the initial nutrient status of the experimental soil is low available nitrogen (270 kg N ha^{-1}) as determined by Kjeldal method, high in available phosphorus (50 kg P_2O_5 ha^{-1}) as determined by Olesen's method and medium in available potassium (254 kg K_2O ha^{-1}) as determined by Flame photometric method (13-15). The soil was found slightly alkaline (pH 7.82) with normal electrical conductivity (0.030 dSm^{-1}) and organic carbon content of 0.73 % (16).

The experiment followed a split-plot design with three replications. The main plots comprised five sowing dates: D_1 (10 November), D_2 (25 November), D_3 (10 December), D_4 (25 December) and D_5 (10 January). Subplots included three rice cultivars: V_1-RNR-15048 (short, slender grain, 135-day duration), V_2-KNM-1638 (medium, slender grain, 120-130-day duration) and V_3-JGL-24423 (long, bold grain, 135-day duration). Sprouted seeds were broadcast on well-prepared raised beds at seed rates of 50 kg ha^{-1} (fine-grain) and 62.5 kg ha^{-1} (bold-grain). Seedlings were transplanted at the five-leaf stage with 15 × 15 cm spacing. Fertiliser was applied at 150:60:40 (nitrogen: phosphorus: potassium) NPK kg ha^{-1}.

Model description

The Decision Support System for Agrotechnology Transfer (DSSAT), developed by the IBSNAT (International Benchmark Sites Network for Agrotechnology Transfer) group, is a crop simulation platform that evaluates crop growth, yield and resource balance using soil, weather and management inputs. The CERES-rice model (DSSAT v4.8.5.0) was used to simulate phenology, biomass accumulation, assimilate partitioning, soil water balance, nitrogen dynamics and yield, accounting for both photosynthesis and stress factors. The model was calibrated and validated with field data on crop growth, phenology and yield across different sowing dates.

Input requirements

Implementation of the CERES-rice model required comprehensive datasets on weather, soil, genotype and crop management, all formatted into standard DSSAT input files. Weather data, including daily maximum and minimum temperatures, rainfall and solar radiation, were obtained from the research station and compiled into weather input files. Soil physical and chemical properties within the rooting depth were characterised from a 1 m depth soil profile, analysed layer-wise and processed using the DSSAT Soil Build tool to derive parameters such as texture, organic carbon, pH, water retention limits, bulk density, hydraulic conductivity and root growth factor. Crop management datasets were prepared for each treatment and included details on cultivar, tillage, nursery sowing, transplanting, fertiliser application schedules, irrigation and harvest operations.

Genetic coefficients

The CERES-rice model requires cultivar-specific genetic coefficients, which were estimated from sowing dates that showed optimal growth and yield performance (17). Iterative adjustments were made until simulated phenology, growth and yield closely matched observed values (Table 1) (18).

Statistical analysis

Model performance evaluation was statistically assessed using the absolute Root Mean Square Error (RMSE), normalised Root Mean Square Error (NRMSE) and index of agreement (d-stat).

Root mean square error (RMSE)

The root mean square error (RMSE) quantifies the average deviation between simulated and observed values, serving as a key indicator of model accuracy. Lower RMSE values imply stronger agreement between observed and simulated data, thereby reflecting superior model performance. RMSE is calculated as

Table 1. Genetic coefficients of rice varieties developed and used for the CERES-rice model

S.No.	Description of coefficient	RNR-15048	KNM-1638	JGL-24423
1	**P_1:** Time period (in growing degree days) above a base temperature of 9°C) from seedling emergence during which the rice plant is not responsive to changes in photoperiod.	566.7	685	583.4
2	**P_2O:** Critical photoperiod at which development occurs at a maximum rate.	11.5	12.7	12.7
3	P2R: Extent to which phasic development leading to panicle initiation is delayed (expressed as GDD in °C-d) for each hour increase in photoperiod above P2O.	74.9	218.2	29.8
4	**P_5:** Time period in GDD oC-d) from the beginning of grain filling (3 to 4 days after flowering) to physiological maturity with a base temperature of 9 °C.	212	259.2	271.3
5	**G_1:** Potential spikelet number coefficient as estimated from the number of spikelets per g of main culm dry weight (less leaf blades and sheaths plus spikes) at anthesis.	69.3	70	58.1
6	**G_2:** Single grain weight (g) under ideal growing conditions, i.e. non-limiting light, water, nutrients and absence of pests and diseases.	0.015	0.0166	0.024
7	**G_3:** Tillering coefficient (scalar value) relative to IR64 cultivar under ideal conditions.	0.74	0.80	0.74
8	**PHINT:** Phyllochron interval (°C-d). Time interval in degree-days for each leaf-tip to appear under non-stressed conditions.	80.2	80.0	80.2
9	**THOT:** Temperature (°C) above which spikelet sterility is affected by high temperature.	34.0	33.9	33.7
10	**TCLDP:** Temperature (°C) below which panicle initiation is further delayed (other than P1, P2O and P2R) by low temperature.	15.0	15.0	15.0
11	**TCLDF:** Temperature (°C) below which spikelet sterility is affected by low temperature.	15.0	15.0	15.0

$$\text{RMSE} = \left(\sqrt{\frac{\sum_{t=1}^{n}(\text{Pi} - \boldsymbol{Oi})^2}{n}}\right) \qquad \text{(Eqn. 1)}$$

where n represents the number of observations, O_i denotes the observed values and P_i denotes the simulated values.

Normalised root mean square error (nRMSE)

The normalised root mean square error (nRMSE) expresses RMSE as a percentage of the observed mean ($\bar{O}$, thereby allowing comparison across variables of different scales (19).

$$\text{RMSE}n = \frac{\text{RMSE}}{\bar{O}} \times 100 \qquad \text{(Eqn. 2)}$$

The model prediction accuracy is categorised; the values below 10 % indicate Excellent, values between 10 % - 20 % were considered good, between 20 % - 30 % considered as fair and above 30 % as poor.

Index of Agreement (d- Stat)

The index of agreement measures the degree of fit between observed and simulated values, ranging from 0 (poor) to 1 (perfect) (20).

$$\text{D} = 1- \frac{\sum_{i=1}^{n}(\ (\text{Oi} - \text{Pi})2}{\sum_{i=1}^{n}(|\text{Pi} - \bar{\text{O}}| + |\text{Oi} - \bar{\text{O}}|)} \qquad \text{(Eqn. 3)}$$

Results and Discussion

Genetic co-efficient

The accuracy of a crop model largely depends on cultivar-specific genetic coefficients that define growth duration, photoperiod sensitivity and potential grain weight (21). Precise estimation based on field observations is utilised to derive genetic coefficients, allowing the model to accurately assess a cultivar's yield potential across different environmental and management practices (22). The CERES-rice model was parameterised with cultivar-specific genetic coefficients for RNR-15048, KNM-1638 and JGL-24423, reflecting their distinct phenological and morphological traits (Table 1). Phenological parameters (P_1, P_2O, P_2R, P_5) varied across cultivars, with KNM-1638 exhibiting a higher P_1 (685 GDD) and P_2R (218.2 GDD h^{-1}), indicating a longer vegetative phase and greater sensitivity to photoperiod. Whereas, RNR-15048 (P_1: 566.7, P_2R: 74.9) and JGL-24423 (P_1: 583.4, P_2R: 29.8) showed lower photoperiod sensitivity, indicating greater flexibility across different sowing windows. Grain filling duration (P_5) was longest in JGL-24423 (271.3 GDD). Yield-related traits showed differences in spikelet number (G_1), grain weight (G_2) and tillering capacity (G_3). RNR-15048 showed higher G_1 and moderate G_2, typical of slender-grain types with more spikelets but lighter grains, whereas JGL-24423 had lower G_1 and higher G_2, consistent with bold-grain types producing fewer but heavier grains. KNM-1638 showed intermediate values, indicating balanced yield attributes. These coefficient patterns align well with the known morphological and yield characteristics of the cultivars, confirming the model's realistic representation of grain formation (23).

Model calibration

The DSSAT-CERES Rice model was calibrated for three rice cultivars (RNR-15048, KNM-1638 and JGL-24423) using observed field data on phenology, biomass, grain yield and straw yield (Table 2). Calibration was performed by iteratively adjusting genetic coefficients until simulated and observed values aligned and performance was assessed using RMSE, nRMSE and d-statistics. The model accurately simulated phenology across the cultivars, predicting days to 50 % flowering and maturity within ±1 day of observations. The nRMSE ranged from 1.2-3.7 % for flowering and 1.7-3.0 % for maturity, while d-statistics consistently exceeded 0.83, indicating strong agreement. Biomass predictions showed deviations ranging from –3.6 % and +2.7 %, with RMSE <600 kg ha^{-1}, nRMSE 2.6-5.0 % and d-statistics of 0.82-0.87, confirming good consistency across cultivars and implying that CERES-rice adequately reproduced crop growth rate and assimilate pattern during vegetative and reproductive phases. Grain yield simulation was most accurate, with deviations <2.5 %, calibration errors <6 %,

Table 2. Observed and predicted phenology, total biomass, grain yield and straw yield after calibration of the CERES-rice model for rice

Variable name	Observed	Simulated	NRMSE	RMSE	d-Stat.
RNR-15048					
Days to 50 % flowering (days)	70	71	2.7	1. 90	0.91
Days to physiological Maturity (days)	94	93	1.7	1.61	0.83
Biomass at harvest kg ha^{-1}	11808	11992	2.6	308.5	0.83
Grain Yield kg ha^{-1}	5577	5604	3.4	190.7	0.85
Straw yield kg ha^{-1}	6130	6388	5.1	310.6	0.81
KNM-1638					
Days to 50 % flowering (days)	73	74	3.7	2.7	0.92
Days to physiological Maturity (days)	99	99	3.0	2.9	0.84
Biomass at harvest kg ha^{-1}	10834	11105	4.7	510.9	0.87
Grain Yield kg ha^{-1}	5473	5498	3.5	190.8	0.95
Straw yield kg ha^{-1}	5777	5607	5.7	332.1	0.85
JGL-24423					
Days to 50 % flowering (days)	67	68	1.2	0.78	0.98
Days to physiological Maturity (days)	94	94	2.0	1.89	0.91
Biomass at harvest kg ha^{-1}	11409	11005	5.0	568.8	0.82
Grain Yield kg ha^{-1}	5962	5833	3.6	213.9	0.91
Straw yield kg ha^{-1}	5507	5172	10.5	578.2	0.81

nRMSE 3.4–3.6 %, RMSE <215 kg ha^{-1} and d-statistics >0.85, underscoring the robustness of the model in effectively capturing sink and grain filling processes governed by G_1 (spikelet number) and G_2 (grain weight). Straw yield predictions also showed acceptable accuracy, with deviations from –6.6 % to +4.2 %, nRMSE <10.5 %, RMSE <580 kg ha^{-1} and d-statistics between 0.81 and 0.85. Overall, calibration results confirmed that CERES-rice accurately simulated phenology, biomass and yield across cultivars under rabi conditions, with all error indices remaining within internationally accepted thresholds (nRMSE <10 %) for good to excellent model performance.

Model validation

After calibration, the DSSAT-CERES Rice model was validated using independent datasets to assess its predictive ability across phenology, biomass, grain yield and straw yield for the cultivars RNR-15048, KNM-1638 and JGL-24423 (Table 3 & Fig. 1-5). Statistical evaluation employed RMSE, normalised RMSE (nRMSE) and the index of agreement (d), which collectively provide insight into absolute error, relative accuracy and model fit.

Phenology

The model demonstrated reliable predictions across all cultivars as presented in Fig. 1A-C. In RNR-15048, days to 50 % flowering were slightly overestimated by four days, with an nRMSE of 6.3 % (excellent) and a d-stat of 0.76, suggesting moderate agreement. This small bias could be attributed to the variety's moderate photoperiod sensitivity (low P_2R), which may have interacted with short-day conditions during the post-monsoon period. KNM-1638 showed the best accuracy, with only a one-day deviation (nRMSE 1.8 %, RMSE 1.41 days, d = 0.89), indicating that it requires longer day lengths and performs best under early transplanting. JGL-24423 also exhibited strong agreement, with an error of one day, nRMSE 4.6 % and d = 0.85, consistent with its shorter phenological duration and lower thermal requirement (P_1, P_5). Deviations in physiological maturity were minimal (≤2 days), with nRMSE values between 0.9-3.9 % and d-statistics of 0.81–0.86 (Fig. 2A-C). These results indicated that the calibrated photothermal coefficients (P_1, P_2 and P_5) effectively captured varietal differences in thermal time and photoperiod responses. These findings align with earlier CERES-rice evaluations in temperate Kashmir reported RMSE ~5.0 days for anthesis and ~3.7 days for maturity, while research indicates that phenological simulations are well within global ranges in Kerala (24, 25).

Biomass

The biomass accumulation (Fig. 3A-C), accuracy varied slightly by genotype. RNR-15048 was overestimated (11,868 vs. 11,194 kg ha^{-1}), with nRMSE of 7.5 % and d = 0.71, indicating fair but acceptable performance. KNM-1638 showed moderate overestimation (11,259 vs. 10,698 kg ha^{-1}) with nRMSE of 5.5 % and d = 0.74. JGL-24423 showed the closest match (11053 vs. 10925 kg ha^{-1}), with an nRMSE of 1.8 % and d = 0.83. The slightly higher deviations in RNR-15048 and KNM-1638 may be attributed to their greater tillering capacity and longer vegetative duration, leading to potential overestimation of canopy biomass under favourable soil nitrogen and moisture conditions. Similar patterns were reported that CERES-rice biomass

Table 3. Observed and predicted phenology, total biomass, grain yield and straw yield after validation of the CERES-rice model for rice

Variable Name	Observed	Simulated	NRMSE	RMSE	d-Stat.
RNR-15048					
Days to 50 % flowering (days)	69	73	6.3	4.4	0.76
Days to physiological Maturity (days)	94	95	3.1	2.89	0.86
Biomass at harvest kg ha^{-1}	11194	11868	7.5	844.8	0.71
Grain Yield kg ha^{-1}	5118	5356	5.9	301.9	0.87
Straw yield kg ha^{-1}	6076	6512	9.8	595.5	0.78
KNM-1638					
Days to 50 % flowering (days)	77	78	1.8	1.41	0.89
Days to physiological Maturity (days)	103	103	0.9	0.89	0.81
Biomass at harvest kg ha^{-1}	10698	11259	5.5	584.6	0.74
Grain Yield kg ha^{-1}	4851	5066	8.7	423.9	0.86
Straw yield kg ha^{-1}	5627	6192	11.2	630.7	0.852
JGL-24423					
Days to 50 % flowering (days)	68	69	4.6	3.1	0.85
Days to physiological Maturity (days)	93	95	3.9	3.6	0.84
Biomass at harvest kg ha^{-1}	10925	11053	1.8	194.5	0.83
Grain Yield kg ha^{-1}	5720	6049	7.4	421.1	0.76
Straw yield kg ha^{-1}	4976	5003	6.2	310.3	0.83

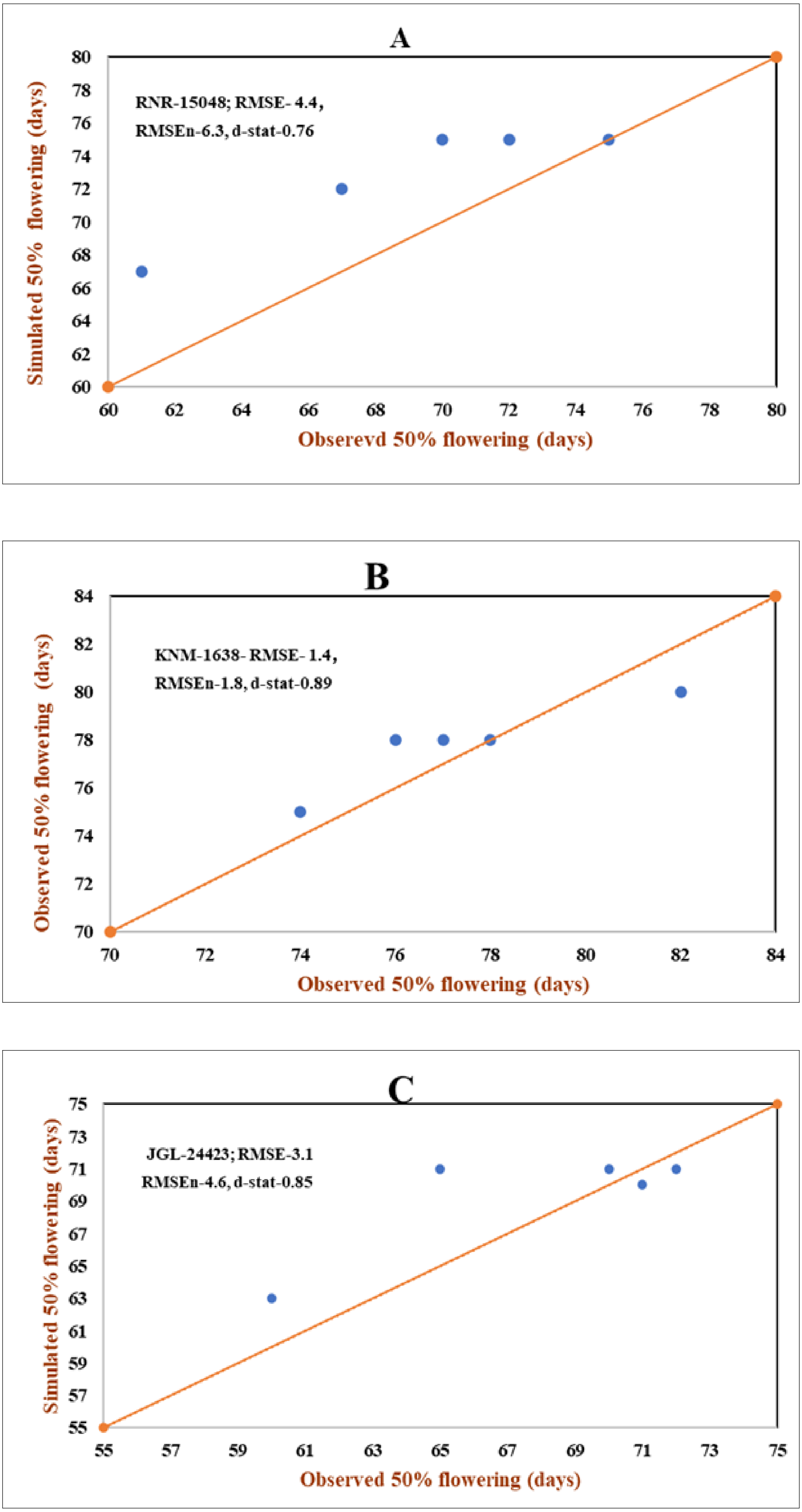

Fig. 1. Comparison of observed and simulated 50 % flowering of variety: **A.** RNR-15048; **B.** KNM-1638; **C.** JGL-24423 after validation.

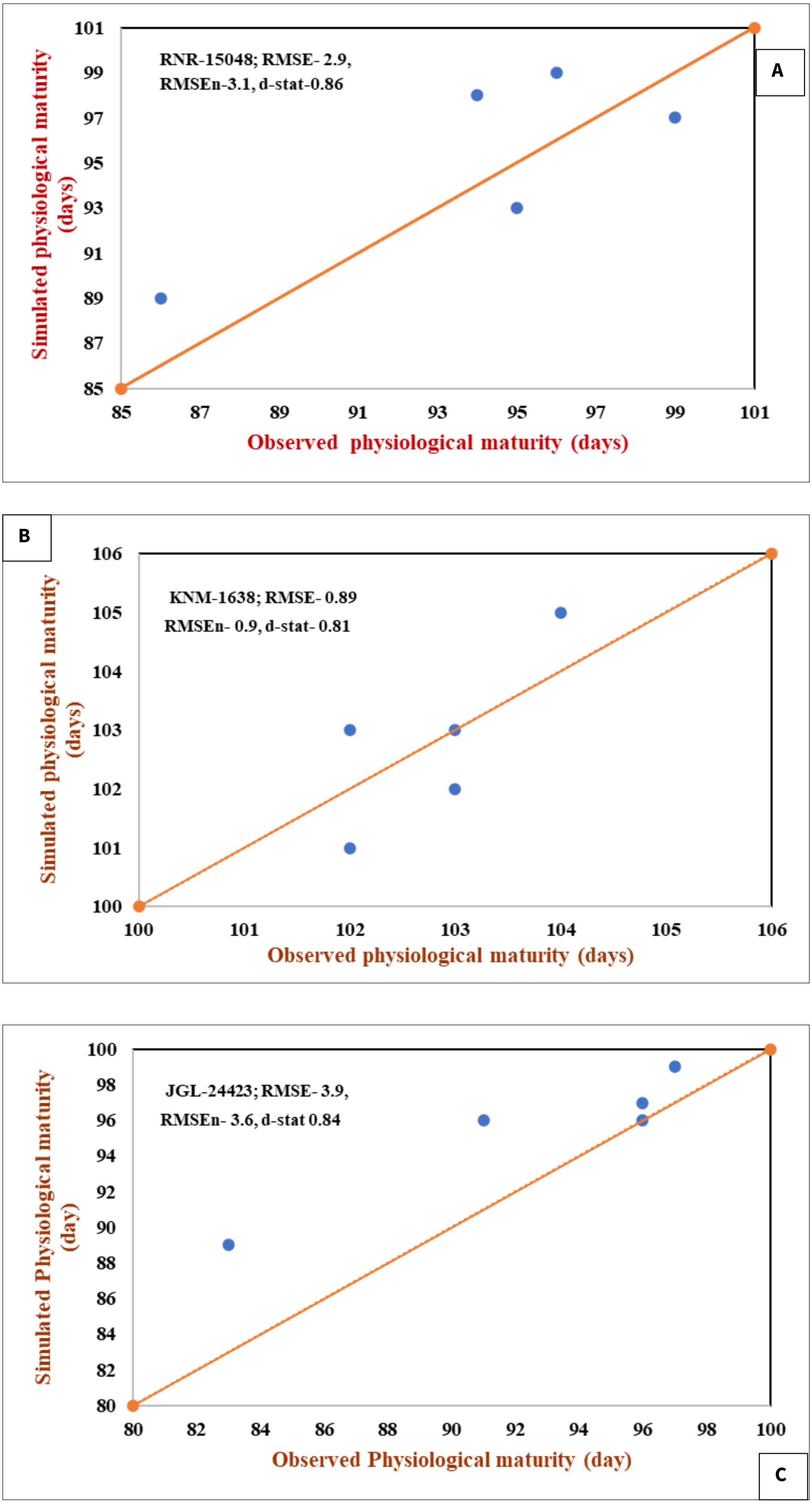

Fig. 2. Comparison of observed and simulated physiological maturity of variety: **A.** RNR-15048; **B.** KNM-1638; **C.** JGL-24423 after validation.

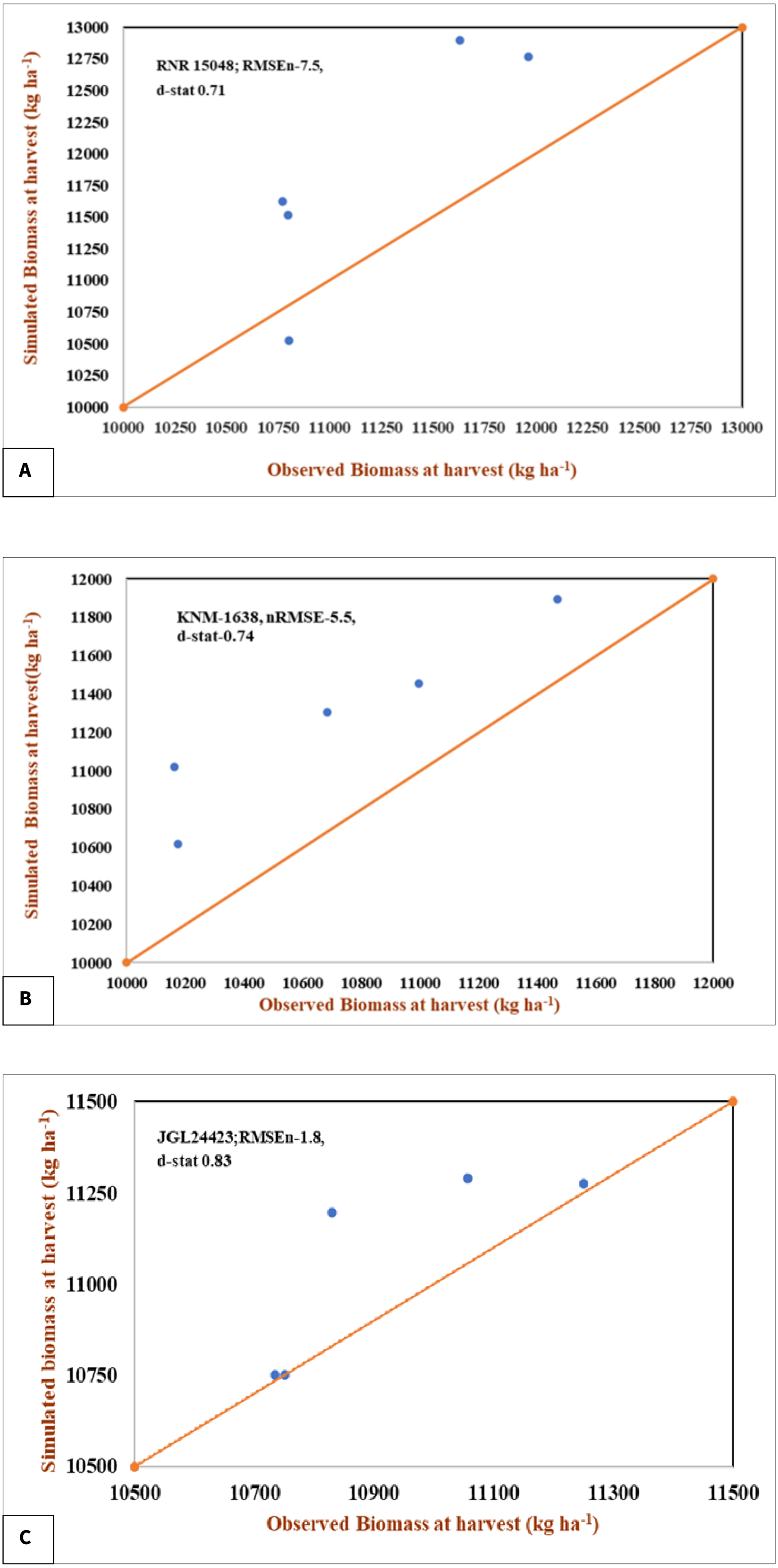

Fig. 3. Comparison of observed and simulated biomass at harvest of variety: **A.** RNR-15048; **B.** KNM-1638; **C.** JGL-24423 after validation.

accuracy is influenced by canopy dynamics and soil nitrogen calibration (26, 27). Despite these differences, all nRMSE values remained below 10 %, demonstrating that CERES-rice reliably captured cultivar-specific biomass accumulation and growth trends under *rabi* conditions.

Grain yield

The grain yield (Fig. 4A-C) predictions were robust but slightly overestimated. RNR-15048 showed the closest agreement (5356 vs. 5118 kg ha^{-1}; nRMSE 5.9 %, RMSE 301.9 kg ha^{-1}, d = 0.87). This agreement suggests that the genetic coefficients (particularly G_1 and G_2) effectively represented its high spikelet density and slender grain type, enabling the model to accurately capture assimilate partitioning toward grain formation. KNM-1638 was overestimated by 4.5 % (nRMSE 8.7 %, RMSE 423.9 kg ha^{-1}, d = 0.86, which may be attributed to its higher tillering potential (G_3) and vigorous canopy growth, leading the model to allocate excessive assimilates toward grain formation under idealized nitrogen and water conditions, while JGL-24423 showed the largest deviation (6049 vs. 5720 kg ha^{-1}; nRMSE 7.4 %, d = 0.76) (27). The deviation due to its bold-grain nature (higher G_2) and shorter grain-filling period (lower P_5), which the model may have slightly underrepresented. However, all values fall within the “good” to “excellent” category (nRMSE <10 %) and are comparable to earlier CERES-rice validations that reported nRMSE values between 5–12 % for grain yield (26).

Straw yield

The straw yield (Fig. 5A-C) variability was greater compared to grain yield, reflecting model sensitivity to biomass partitioning. RNR-15048 was overestimated by 7 % (6512 vs. 6076 kg ha^{-1}; nRMSE 9.8 %, RMSE 595.5 kg ha^{-1}, d = 0.78). KNM-1638 showed the largest deviation (6192 vs. 5627 kg ha^{-1}; nRMSE 11.2 %, fair category, d = 0.85). In contrast, JGL-24423 was closely aligned (5003 vs. 4976 kg ha^{-1}; nRMSE 6.2 %, RMSE 310.3 kg ha^{-1}, d = 0.83). The relatively higher deviation in KNM-1638 may be attributed to its vigorous vegetative growth and high tillering capacity (reflected by its higher G_3 coefficient), which could have led the model to overestimate the partitioning of assimilates toward vegetative organs under non-limiting nutrient and water conditions. The CERES-rice model uses fixed partitioning coefficients during the pre- and post-anthesis phases; hence, it may inadequately capture genotype-specific variation in carbohydrate translocation from stems to grains (27). In contrast, the model performed better for JGL-24423, which possesses moderate vegetative growth and compact canopy structure, suggesting that CERES-rice more accurately represents assimilate partitioning in genotypes with balanced source–sink relationships. Similar findings were reported in earlier studies observed 8–12 % variation in straw yield prediction, comparable to the present study (27, 28). Overall, validation confirmed that the CERES-rice model reliably simulates phenology and grain yield with high accuracy across all cultivars, while biomass predictions are consistent but somewhat genotype-dependent. Straw yield remains more variable, particularly for KNM-1638, though still within acceptable limits. With most nRMSE values <10 % and d-statistics >0.70, the model performance aligns well with international evaluations, confirming that the calibrated genetic coefficients are physiologically realistic and the model is robust for rabi rice simulation.

Conclusion

The calibration and validation of the DSSAT-CERES Rice model confirmed its robustness in simulating phenology, biomass, grain yield and straw yield of three rice cultivars across different sowing dates under *Rabi* conditions. Phenological stages and grain yield were predicted with high accuracy (nRMSE <10 %, d >0.80), while biomass simulations were reliable but moderately genotype-dependent. Straw yield showed greater variability, particularly for KNM-1638, reflecting the model’s sensitivity to biomass partitioning processes. The calibrated genetic coefficients were physiologically realistic and consistent with reported ranges for Indica rice. Overall, the CERES-rice model proved effective for yield forecasting, crop management optimisation and climate adaptation studies in Telangana.

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Authors' contributions

BMB contributed to the conceptualisation, data curation, methodology development, validation, supervision and editing of the manuscript. RK contributed to the conceptualisation, data curation, methodology development, validation, supervision and editing of the manuscript. BBN contributed to the conceptualisation, data curation, methodology development, validation, supervision and editing of the manuscript. GD contributed to the conceptualisation, data curation, methodology development, validation, supervision and editing of the manuscript. KSB provided resources and contributed to the visualisation. DV contributed to methodology development and manuscript editing. MK contributed to the editing of the manuscript. GR provided resources and contributed to manuscript editing. AKC provided resources and contributed to manuscript editing. GN provided resources and contributed to manuscript editing. All authors read and approved the final version of the manuscript.

Compliance with ethical standards

Conflict of interest: Authors do not have any conflict of interests to declare.

Ethical issues: None

Declaration of generative AI and AI-assisted technologies in the writing process

During the development of this work, the author(s) used ChatGPT to refine the language and improve readability. The content was subsequently reviewed and edited as needed and the author takes full responsibility for the content of the publication.

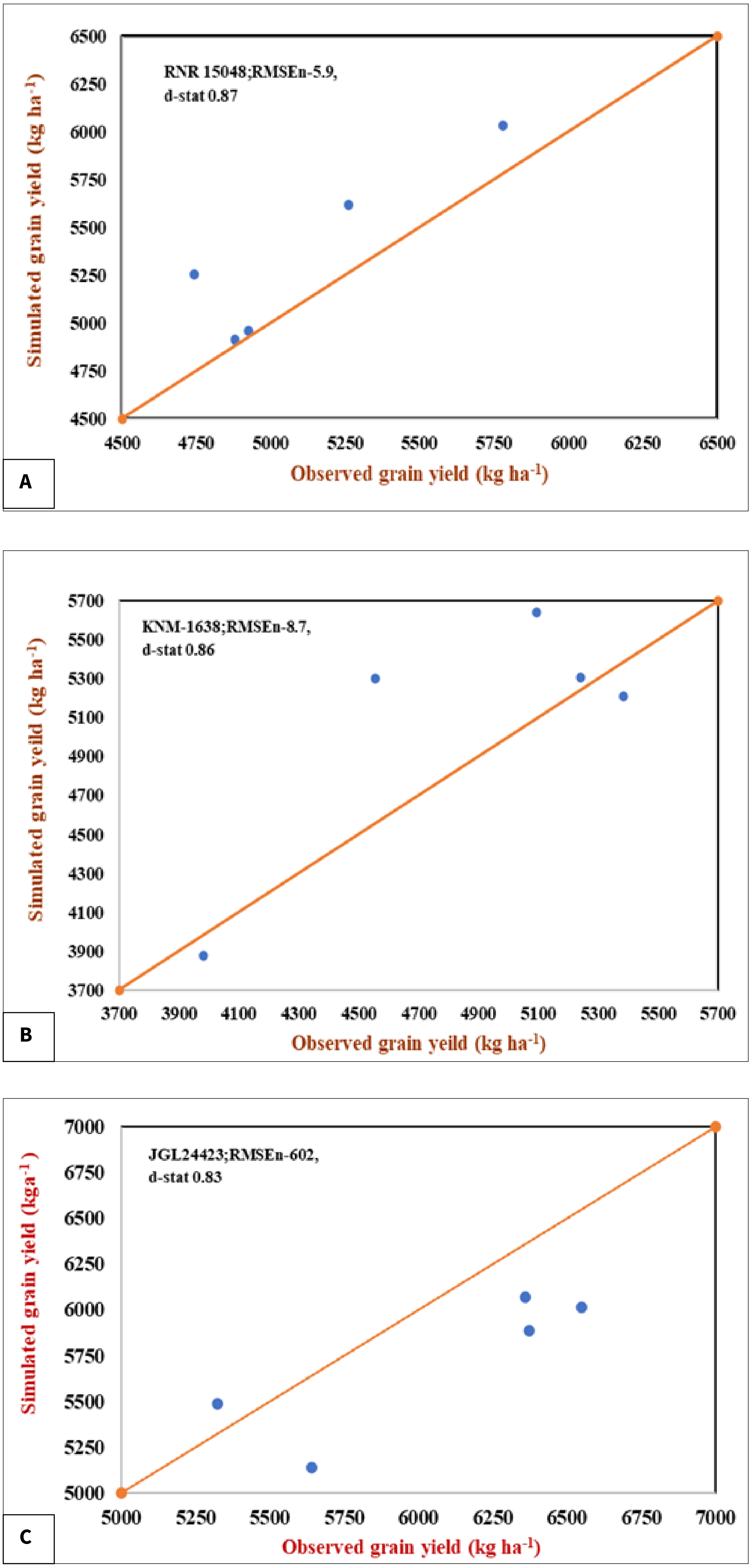

Fig. 4. Comparison of observed and simulated grain yield at harvest of variety: **A.** RNR-15048; **B.** KNM-1638; **C.** JGL-24423 after validation.

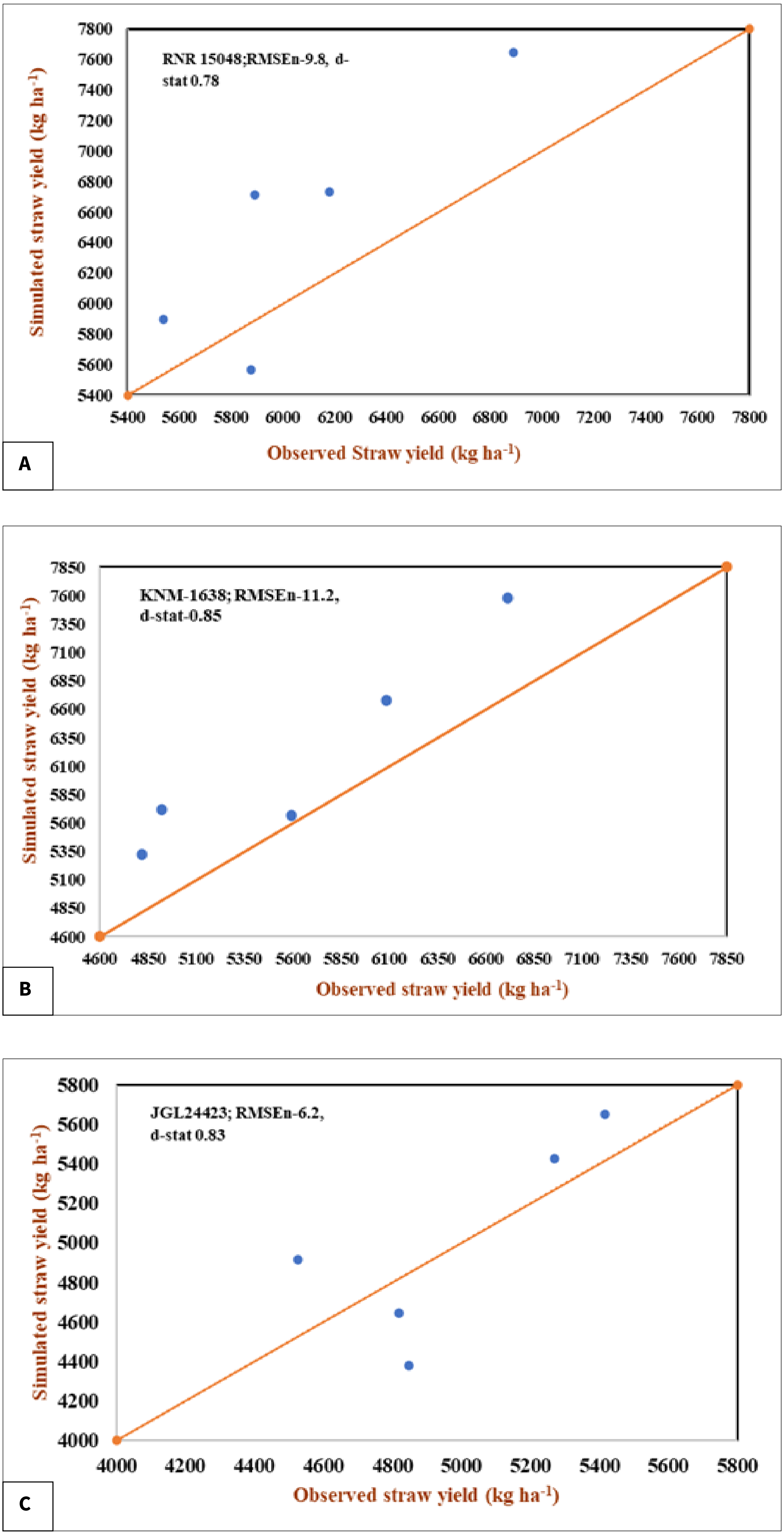

Fig. 5. Comparison of observed and simulated straw yield at harvest of variety: **A.** RNR-15048; **B.** KNM-1638; **C.** JGL-24423 after validation.

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