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Field Validation of the DNDC-Rice Model for Crop Yield, Nitrous Oxide Emissions and Carbon Sequestration in a Soybean System with Rye Cover Crop Management

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Abstract: The DNDC-Rice model effectively simulates the yield and greenhouse gas emissions within paddy system, while its performance under upland conditions remains unclear. This study validated the model using data from a long-term cover crop experiment (fallow [FA] and rye [RY]) in a soybean field, evaluating its limitations in upland systems simulation. The model underestimated water-filled pore space (WFPS) and nitrous oxide (N_2O) flux while overestimating soybean biomass, yield, and carbon dioxide (CO_2) flux. The underestimation of cumulative N_2O flux (25.6% in FA and 5.1% in RY) was attributed to both underestimated WFPS and algorithm's limitations in simulating N_2O emission pulses. Overestimated soybean growth increased respiration, leading to the overestimation of CO_2 flux. Although the model captured trends in soil organic carbon (SOC) stock, the simulated annual values differed from observations (-9.9% to +10.1%), potentially due to sampling errors. Both observed and simulated results showed that RY increased N_2O emissions and SOC stock compared to FA. However, enhanced SOC sequestration under RY offset the increased N_2O emissions, resulting in a lower net global warming potential than FA. These findings indicate that the DNDC-Rice model requires improvements in its nitrogen cycling algorithm and crop growth sub-models to improve predictions for upland systems.

Keywords: DNDC-Rice; greenhouse gas; soil organic carbon; cover crop

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1. Introduction

Agricultural production is a significant source of greenhouse gas (GHG) emissions, which are key drivers of climate change [1]. Extreme climate events, in turn, reduce agricultural yields, thereby threatening global food security [2]. Agricultural soils can function as either sources or sinks of GHGs, depending on various conditions [3]. Implementing effective agricultural management practices to reduce GHG emissions and enhance carbon sequestration is a crucial strategy for mitigating climate change at the agricultural level.

In recent years, conservation agricultural management practices have rapidly spread due to their ability to enhance ecosystem services and promote sustainable agricultural development [4]. Cover crop management, a typical and historic conservation agriculture method, massive studies have confirmed its positive effect on mitigating soil erosion [5], improving soil structure and water-stable aggregates [6,7], enhancing soil fertility [8] and reducing weeds infestation [9,10]. For example, a cover crop experiment conducted in Japan demonstrated that a rye cover crop significantly improved soil health within a soybean cropping system [11]. However, the impact of cover crops on GHG emissions and soil carbon sequestration remains contentious. Some studies have reported that cover crops can reduce nitrous oxide (N_2O) emissions by scavenging excess NO_3-N in the soil [12,13]. The biomass remaining after cover crop termination serves as a carbon source, contributing to increased soil organic carbon (SOC) stocks [14,15]. However, the release of organic carbon and nitrogen during the decomposition of cover crop residues may also result in elevated N_2O emissions [16,17]. These increased N_2O emissions, in turn, could potentially offset the climate change mitigation benefits associated with the enhanced SOC stocks [18,19]. The potential of cover crops to mitigate climate change varies based on factors such as site characteristics, agronomic practices, and cover crop species [18,20]. Consequently, evaluating the effect of cover crops on climate change requires incorporating context-specific considerations.

Although field experiments can provide direct observations of GHG emissions and SOC stock at a specific point in time, they are difficult to use for continuous monitoring of intermediate processes, such as the carbon-nitrogen-water-crop balances [21]. Additionally, field experiments are resource-intensive and time-consuming due to the necessity of conducting extensive repeated measurements [22]. A well-calibrated model has the capacity to simulate the physical, chemical, and microbiological processes in soil using mathematical principles and computational power to calculate soil GHG emissions [23]. Simulation models are diverse, varying in complexity from simple empirical estimates based on statistical analysis to complex process-based biogeochemical models [23,24]. The DeNitrification-Decomposition (DNDC) model, a process-based model, focus on the carbon and nitrogen biogeochemistry in agro-ecosystem [25]. By integrating classical physic, chemistry and biology laws, the model is capable of parameterizing specific geochemical or biochemical processes, such as simulating and quantifying the GHG emissions, as well as carbon and nitrogen dynamics in soil [26]. Currently, the DNDC model is widely adopted to estimate and compare the GHG mitigation potential across diverse agricultural management scenarios at regional and national scales [27,28]. Moreover, the DNDC model has been modified numerous times and integrated with various sub-models to produce different versions to meet the specific needs of different regions, agronomic management and crops. For instance, DNDC-Rice is a revised version specifically designed for rice cultivation [29]. The DNDC-Rice model significantly enhances the ability to estimate greenhouse gas emissions from paddy fields and has been validated using GHG data from paddy fields across Asia, including Japan [30], India [31], and Thailand [32]. It demonstrates high accuracy and performance in simulating and predicting greenhouse gas emissions from paddy fields under different irrigation management scenarios [31].

In rice production systems, alongside the prevalent practice of continuous rice monoculture, the rotation of paddy with upland crops is also commonly employed [33]. Numerous studies have reported that the DNDC-Rice model is a powerful tool for accurately estimating soil GHG emissions in the continuous rice monoculture system [28,34]. In rice systems with paddy-upland rotation, it is impractical to use different versions of the DNDC model to simulate and predict the paddy and upland periods separately. However, field validation of the DNDC-Rice model for N_2O emissions in upland cropping systems remains limited. Furthermore, previous studies have primarily focused on estimating GHG emissions, while field validations concerning the dynamics of carbon sequestration are still scarce.

Thus, we conducted a field validation of the DNDC-Rice using data from a long-term soybean-cover crop cropping system. This study aims to address the gap in the validation of the DNDC-Rice model for upland systems, thereby advancing its application in simulating paddy-upland rotation systems. Specifically, the objectives of this study were to: (1) evaluate the performance of the DNDC-Rice model in simulating N_2O emissions and soil organic carbon stock dynamics in an upland cropping system with a cover crop; and (2) discuss the strategies to improve the accuracy of the predictions.

2. Materials and Methods

2.1. The DNDC-Rice Model

The DNDC model is a process based model to simulate greenhouse gases, such as nitrous oxide, carbon dioxide and methane, from agricultural ecosystems [26] by focusing on the carbon and nitrogen biogeochemistry in agro-ecosystem [25]. DNDC consists of six sub-models divided among two components. The first component consists of soil climate, plant growth, and decomposition sub-models. These sub-models are driven by ecological drivers (i.e. climate, soil, vegetation, and human activity) and predict soil environmental factors (e.g. temperature, moisture, pH, substrate concentrations). The second component consists of denitrification, nitrification, and fermentation sub-models. These sub-models predict gas fluxes (CO_2, CH_4, NH_3, NO, N_2O, and N_2) through denitrification, nitrification, and CH_4 production and oxidation processes [26,35,36].

DNDC-Rice is a revised DNDC model to simulate CH_4 emission from rice paddies [29,30]. The revised model quantifies the production of electron donors [H_2 and dissolved organic carbon (DOC)] by decomposition and rice root exudation, and simulates CH_4 production and other reductive reactions based on the availability of electron donors and acceptors (NO_3^-, Mn^{4+}, Fe^{3+}, and SO_4^{2-}) under anaerobic soil processes. Rice growth process and methane emission through rice by a diffusion routine were also modified in DNDC-Rice.

In this study, we used DNDC-Rice model to simulate a soybean system with rye cover crop management and to improve the simulation results by modifying the source codes. DNDC-Rice simulation was conducted for the period of 1987-2022 with the input of measured soil properties, daily meteorological data and the field managements at the experimental site. Carbon input from plant biomass to the soil was simulated as application of straw or green manure based on measured biomass of soybean residue, rye and natural weed.

2.2. Modification and Initialization of the Model

At first, the maximum tillage depth was changed: the maximum tillage depth in DNDC-Rice was 20 cm depth, and it was changed to 30 cm same as field practice. During the validation, it was found that DNDC-Rice simulated soil carbon decomposition too fast and tillage strongly affected to soil carbon decomposition. Therefore, tillage factor was changed from the default of 1.5 to 1.0. Deepest tilled layer number also modified. In the DNDC, the deepest tilled layer was set to be 3 when it was less than 3, but it was modified to be 1 when it was less than 1 to decrease tillage effect to SOC decomposition. We also modified temperature limit, T_limit, which was the based degree to calculate thermal degree days (TDD). T_limit for rye was decreased from 10 to 4.4 based on Mirsky et.al [37] to improve the growth.

In simulating nitrification process in soil, DNDC-Rice assumes that fixed portion of nitrified N is lost as N_2O and NO [26]. After validation of SOC, crop growth, and CO_2 emission, these factors for nitrification-induced N_2O and NO production were changed from 0.015 and 0.0025 to 0.00015 and 0.006, respectively, to minimize the RMSE of simulated daily N_2O emissions from the RY system .

2.3. Experiment Site

We used a long-term cover crop experiment data, initiated in 2003, at the farm of the Center for International Field Agriculture Research and Education, Ibaraki University, Japan. The site lacates in a humid subtropical climate, where the average annual precipitation was 1373 mm and the mean daily temperature was 14.5°C throughout the experimental period (2003–2021) (Figure 1). According to the World Reference Base for Soil Resources, the soil in this region is classified as a typical Andosol. Further details about the site description and soil parameters can be found in Higashi et al. [38].

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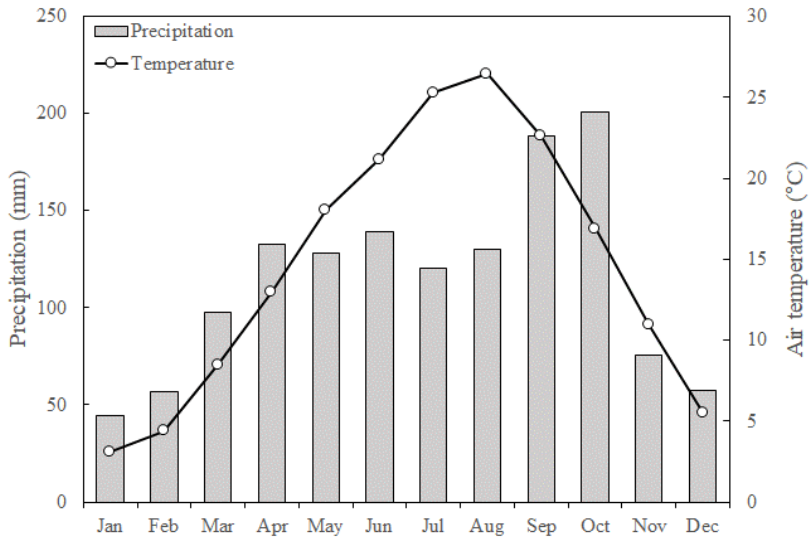

Figure 1. Average monthly precipitation and air temperature from 2008 to 2022.

2.4. Experiment Design and Field Management

In this experimental field, experiments have been concurrently conducted, employing a range of tillage methods and fertilization management practices. In the present study, the field data were collected from the sub-plot that adopted moldboard plowing without fertilization. Tillage was implemented in the summer and autumn using a moldboard plow to a depth of 30 cm. The main crop in the field experiment was upland rice from 2003 to 2007, after which it was replaced by soybean in 2008. In this study, two cover crop management practices [fallow (FA) and rye (RY)] were compared within the soybean system, with four replications for each treatment. Soybean (cv. Sachiyuta) was planted between July and November at a seeding density of 60 kg ha−1. During the cover crop season (November to June), rye (cv. Ryokusei) was sown in the RY plots at a seeding rate of 100 kg ha−1, whereas the FA plots received no artificial intervention, allowing weeds to grow naturally (Table 1). All of main crop residues and cover crop biomass was plowed into the soil. Further details on tillage, crops, and management practices are provided in Gong et al., Higashi et al and Huang et. al. [38–40].

Table 1. Field management schedule for the 2020 and 2021 cropping years. Dates are described as Day/Month/Year.

Management	2020	2021
Summer tillage	2020/6/8	2021/6/14
Soybean sowing	2020/6/30	2021/7/20
Soybean harvest	2020/11/5	2021/11/2
Autumn tillage	2020/11/6	2021/11/3
Cover crop sowing	2020/11/9	2021/11/3
Cover crop harvesting	2021/6/8	2022/5/30

2.5. Soil and Crop Measurement

Soybean samples were collected from the center of each plot using a 0.6 m² quadrat on the day of harvest. Biomass was determined by weighing the oven-dried samples. The oven-dried samples were then threshed, and the grains were weighed for yield analysis. Aboveground biomass from both rye cover crops in RY plots and natural weeds in FA plots was collected prior to summer tillage using a 0.25 m² quadrat. These plant materials were oven-dried to constant mass and weighed to determine dry biomass.

Soil core samples were taken from each plot at a depth of 30 cm in October each year for the measurement of SOC. The samples were dried, ground, and analyzed for SOC content using a C/N analyzer. SOC stock was subsequently determined based on SOC content, depth, and soil bulk density using the soil mass equivalent method [41]. Soil temperature at a depth of 0-5 cm was continuously monitored from 2020 to 2021 using soil temperature sensors. Soil volumetric water content was measured during each gas samples collection to determine the water-filled pore space (WFPS) at a depth of 5 cm. More details regarding the measurement and calculation processes for soybean and soil samples can be found in Gong et al., Higashi et al and Huang et. al. [38–40].

2.6. Greenhouse Gas Measurement

N_2O and CO_2 emissions were monitored from June 2020 to May 2022. Weekly gas samples were collected using the static closed chamber method and analyzed with a gas chromatograph to quantify the concentrations of N_2O and CO_2. Daily fluxes were determined using a concentration-time linear function, while cumulative emissions were calculated through linear interpolation. Further details on the collection, measurement and calculation of gas samples are shown in Huang et al and Ratih et al [40,42].

The net global warming potential (GWP) in agricultural systems consists of greenhouse gas emissions and variation in SOC stock (ΔSOC). The calculation of the net GWP for the period 2020-2021 is as follows:

$$GWP_{2020/2021}(CO_2\ equivalent\ kg\ ha^{-1}\ year^{-1}) = 265 \times cumulative\ N_2O\ emission_{2020/2021} \quad (1)$$

$$\Delta SOC\ (CO_2\ equivalent\ kg\ ha^{-1}\ year^{-1}) = \frac{SOC\ stock_{2021} - SOC\ stcok_{2019}}{2} \times \frac{44}{12} \quad (2)$$

$$Net\ GWP_{2020-2021}\ (CO_2\ equivalent\ kg\ ha^{-1}\ year^{-1}) = \frac{GWP_{2020} + GWP_{2021}}{2} - \Delta SOC \quad (3)$$

where 265 represents the GWP indicator for N_2O conversion to CO_2 over a 100-year period.; 44/12 denotes the conversion factor for converting C to CO_2.

2.7. Statistical Analysis

The simulated results, including daily soil temperature, daily water-filled pore space (WFPS), daily N_2O flux, daily CO_2 flux, SOC stock, soybean biomass, and soybean yield, were assessed using the root mean square error (RMSE) calculated as follows:

$$RMSE = \sqrt{\frac{\sum(\alpha_i - \beta_i)^2}{N}} \quad (4)$$

where αi and βi denote the simulated and observed values of parameter i; and N denotes the number of samples. The normalized RMSE (nRMSE) was also used in this study to evaluate the accuracy of the model simulations and was calculated as follows:

$$nRMSE\ (\%) = \frac{RMSE}{\bar{\beta}} \times 100 \quad (5)$$

where $\bar{\beta}$ is the average of the observed values.

3. Results

3.1. Soil Temperature and Water-Filled Pore Space

The DNDC-Rice model effectively estimated the daily soil temperature at a depth of 0-5 cm for both the FA and RY system during the experimental period, with minimal difference between observed and simulated results (Figure 2). The nRMSE of daily soil temperature in FA system was 10.7%, while in RY system was 11.4% (Table 2). The mean simulated soil temperature was marginally higher than the mean observed temperature, with an increase of 2.1% in FA and 1.6% in RY. Overall, the model accurately captured the seasonal fluctuations in soil temperature throughout the year. However, it consistently tended to overestimate soil temperature during the winter months. Field observations across different systems revealed that the mean daily soil temperature in the RY system was 1.7% higher than in the FA system. Similarly, the model replicated this difference, showing a 1.2% higher simulated value for the RY system compared to the FA system.

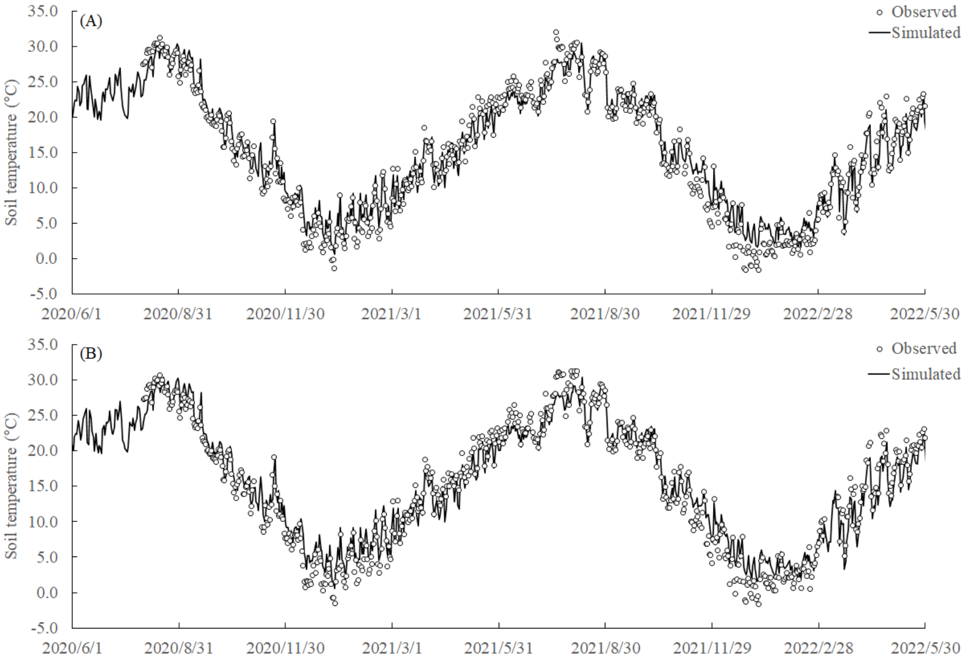

Figure 2. Comparisons between observed and simulated daily soil temperature under fallow (A) and rye (B) system during the 2020 and 2021 cropping year.

Table 2. Observed and simulated mean soil temperature, water-filled pore space (WFPS), daily N_2O emission and daily CO_2 emission during the 2020 and 2021 cropping year. FA: fallow; RY: rye; SD: standard deviation; nRMSE: normalized root mean square error.

Variables	Units	Treatment	n	Observed value		Simulated value		nRMSE (%)
				Mean	SD	Mean	SD	
Soil temperature	°C	FA	678	14.98	0.34	15.29	0.31	10.69
		RY	682	15.24	0.34	15.48	0.31	11.39
WFPS	%	FA	63	32.15	1.39	30.17	0.98	42.67
		RY	63	33.37	1.18	32.56	1.13	41.90
Daily N_2O emission	kg N ha^{-1}	FA	62	1.28	0.17	0.91	0.06	105.16
		RY	63	1.69	0.21	1.63	0.13	94.93
Daily CO_2 emission	kg C ha^{-1}	FA	61	9.07	0.77	10.07	0.99	60.16
		RY	61	14.55	1.26	25.77	1.90	101.31

The DNDC-Rice model successfully simulated the trend of daily WFPS (0-5 cm), although the simulated values were underestimated compared with observed WFPS on average (Figure 3). In the FA system, the mean simulated WFPS was 6.2% lower than the mean observed value, while in the RY system, it showed a 2.5% reduction compared to the mean observed WFPS (Table 2). For all cropping systems, the model overestimated the daily WFPS during winter-spring season but underestimated it during summer-autumn season. In this study, the nRMSE of WFPS in FA system was 42.7%, while in the RY system was 41.9%. The observed mean daily WFPS in the FA system was

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3.7% lower compared to the RY system, and the model also captured this trend, with the simulated value for the FA system being 7.3% lower than that for the RY system.

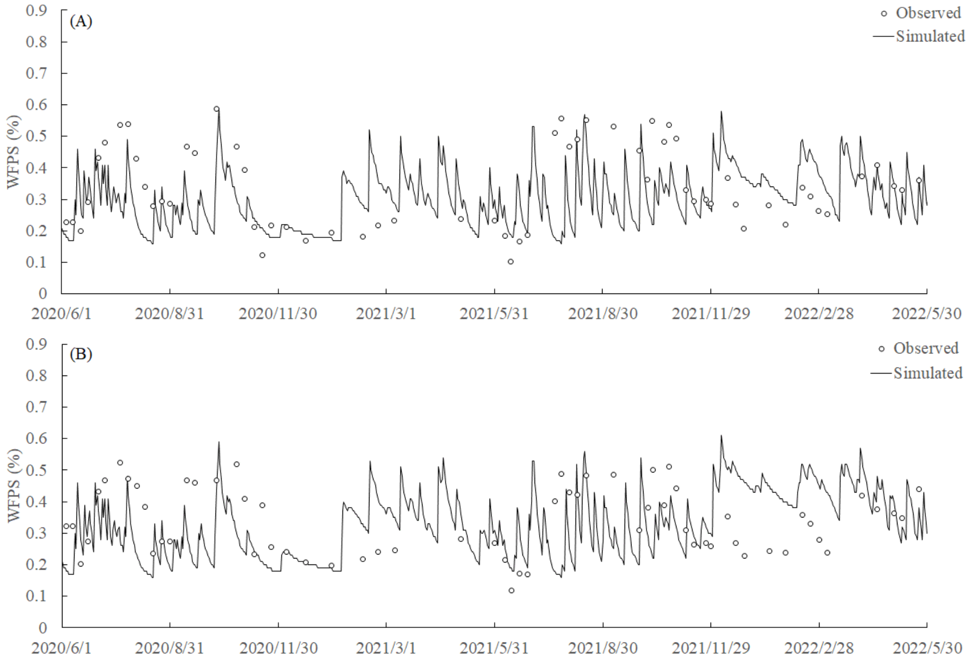

Figure 3. Observed and simulated daily water-filled pore space (WFPS) under fallow (A) and rye (B) system during the 2020 and 2021 cropping year.

3.2. Crop Productivity

In order to validate the model performance on simulating crop productivity, we calculated the average biomass and yield of soybean from 2008 to 2021 compared with simulated values (Table 3). The DNDC-Rice model generally simulated soybean yields accurately in both the FA and RY systems, despite a slight overestimation of the mean simulated values. In the FA system, the model overestimated the mean soybean yield by 3.4%, with a nRMSE of 17.4%. Similarly, in the RY system, the average simulated soybean yield was 12.0% higher compared to observed value, with an nRMSE of 17.2%. On the other hand, DNDC-Rice model overestimated the soybean biomass for both the cropping system. Specifically, the simulated soybean biomass for FA was 15.1% higher than the observed value, whereas for RY it was 18.4% higher. The nRMSE for soybean biomass was 25.5% for FA and 23.5% for RY.

Based on field observations, RY tended to reduce the biomass and yield of soybean, resulting in a 3.2% decrease in mean biomass and an 8.8% decrease in mean yield compared to FA. In contrast, the difference in simulated biomass and yield between FA and RY was minimal, with FA showing only a 0.5% increase.

Table 3. Observed and simulated mean soil organic carbon (SOC) stock, soybean biomass and soybean yield from 2008 to 2021. FA: fallow; RY: rye; SD: standard deviation; nRMSE: normalized root mean square error.

Variables	Units	Treatment	n	Observed value		Simulated value		nRMSE (%)
				Mean	SD	Mean	SD	
Soybean biomass	Mg C ha^{-1}	FA	13	3.23	0.23	3.72	0.16	25.52
		RY	13	3.13	0.18	3.70	0.16	23.52
Soybean yield	Mg C ha^{-1}	FA	13	1.35	0.11	1.39	0.06	17.44
		RY	13	1.24	0.10	1.38	0.06	17.21
SOC stock	Mg C ha^{-1}	FA	13	80.41	0.88	78.76	0.05	5.38
		RY	13	88.48	1.38	90.43	1.34	4.95

3.3. Soil Organic Carbon and Carbon Dioxide Emission

In the present study, the DNDC-Rice model effectively simulated the variation in SOC stock from 2008 to 2021 (Figure 4 and Table 3). In FA system, the observed and simulated average SOC stock were 80.4 Mg C ha^{-1} and 78.8 Mg C ha^{-1}, with a nRMSE of 5.4%. In the RY system, the nRMSE for average SOC stock was 5.0%, with the simulated value (90.4 Mg C ha^{-1}) being 2.2% higher than the observed value (88.5 Mg C ha^{-1}). Additionally, both the observed and simulated SOC stocks in RY were higher than those in FA, with increases of 10.0% and 14.8%, respectively.

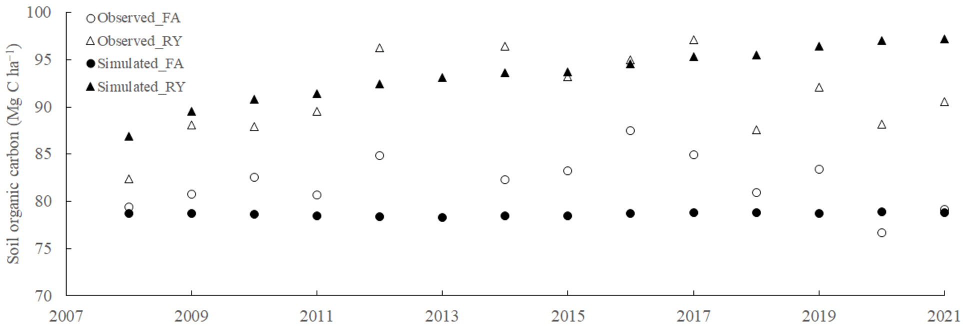

Figure 4. Observed and simulated SOC stock under fallow (FA) and rye (RY) system from 2008 to 2021.

During field observations, surface vegetation within the chamber area was carefully removed to exclude photosynthetic CO_2 uptake. Therefore, the observed CO_2 emission presumably consisted of soil respiration and root respiration, and was compared with simulated CO_2 emissions as the sum of soil respiration and root respiration. The DNDC-Rice model reasonably simulated the trend of daily CO_2 emissions across all cropping systems, although it tended to overestimate the actual daily value (Figure 5). The mean simulated daily CO_2 emissions for FA system was 11.1% higher than the observed value, with a nRMSE of 60.2%. In RY system, the model overestimated the mean daily CO_2 by 77.1%, resulting in a nRMSE of 101.3% (Table 2). Additionally, the simulated daily CO_2 flux increased rapidly following each tillage operation.

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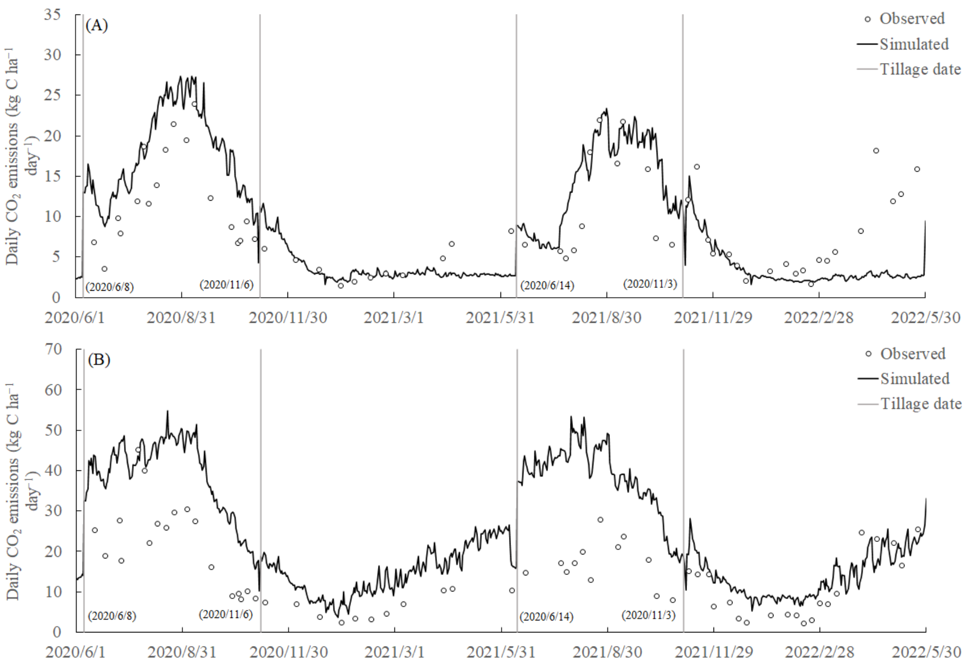

Figure 5. Observed and simulated daily CO_2 emission under fallow (A) and rye (B) system during the 2020 and 2021 cropping year. The gray vertical line, perpendicular to the x-axis, indicates the date of tillage implementation.

Regarding cumulative CO_2 emissions, the model's performance exhibited seasonal variation in the FA system (Table 4). Specifically, during the soybean season, the model overestimated cumulative CO_2 emissions by 42.4% in 2020 and 27.3% in 2021. However, during the cover crop season, the model underestimated cumulative CO_2 emissions, with reductions of 21.3% in 2020 and 53.0% in 2021. In contrast, for the RY system, the model consistently overestimated cumulative CO_2 emissions across all seasons, resulting in an average overestimation of 75.5%. Field observations revealed that the FA system exhibited lower daily CO_2 emissions and total cumulative CO_2 emissions, reducing 38% and 34.2%, respectively, compared to the RY system. The model also captured this trend, amplifying the difference, with daily CO_2 emissions and total cumulative CO_2 emissions in the FA system being 60.9% and 62.0% lower, respectively, than those in the RY system.

Table 4. Observed and simulated cumulative CO_2 emission in each crop season under different cropping system from 2020 to 2021. FA: fallow; RY: rye.

Variable	Treatment	Observed	Simulated
		kg C ha^{-1}	
2020 Soybean season	FA	1701.37	2422.93
	RY	2869.44	4979.66
2020 Cover crop season	FA	951.51	748.77
	RY	1485.84	3133.97
2021 Soybean season	FA	1421.41	1809.51
	RY	1841.09	3999.32
2021 Cover crop season	FA	1554.02	730.55
	RY	2360.57	2905.00
Total cumulation	FA	5628.32	5711.76

	RY	8556.94	15017.95

3.4. Soil Nitrous Oxide Emission

In both the FA and RY systems, the DNDC-Rice model effectively captured the seasonal variation trends of daily N_2O emissions throughout the experimental period (Figure 6). However, the model exhibited a poor fit of daily N_2O emission between the simulated and observed value, with the high nRMSE value (105.2% in FA and 94.9% in RY) (Table 2). Compared to mean observed daily N_2O emission, the simulated value decreased by 28.9% in the FA system, while in the RY system, the reduction was 3.5%. The model consistently underestimated the cumulative N_2O emissions for the FA system across all crop seasons (Table 5). In the case of the MP system, the cumulative N_2O emissions were underestimated during the soybean season, but overestimated during the cover crop season. Overall, the simulated total N_2O emissions were 25.6% lower than the observed values for the FA system and 5.1% lower for the RY system. Moreover, both the simulated and observed values indicated that the daily N_2O flux and total N_2O emissions under the FA system were lower than those under the RY system, with reductions ranging from 24.3% to 62.0%.

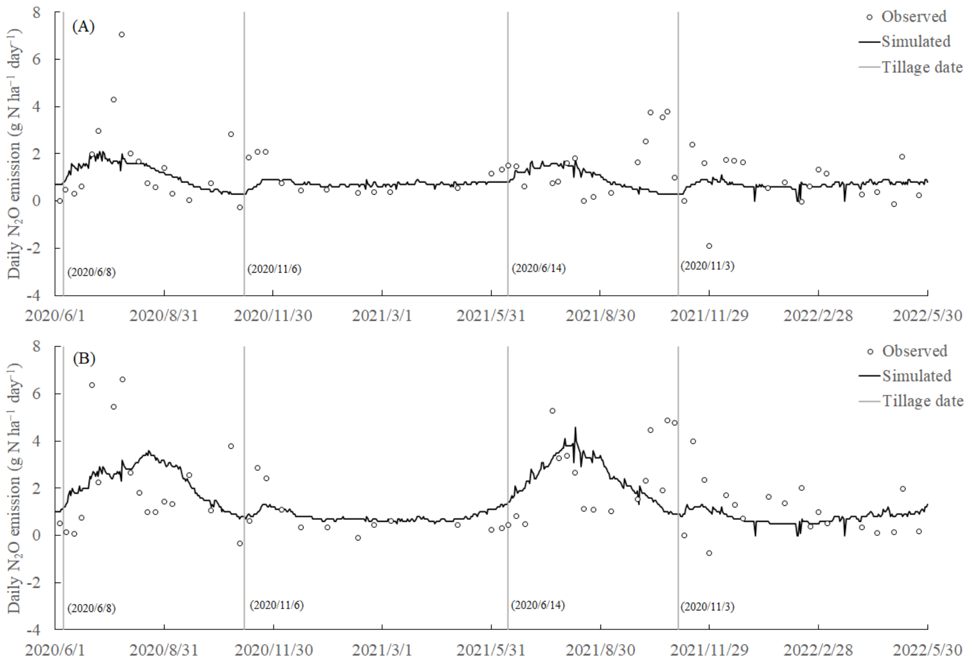

Figure 6. Observed and simulated daily N_2O emission under fallow (A) and rye (B) system during the 2020 and 2021 cropping year. The gray vertical line, perpendicular to the x-axis, indicates the date of tillage implementation.

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Table 5. Observed and simulated cumulative N_2O emission in each crop season under different cropping systems from 2020 to 2021. FA: fallow; RY: rye.

Variable	Treatment	Observed	Simulated
		kg N ha^{-1}	
2020 Soybean season	FA	231.73	142.80
	RY	335.18	300.30
2020 Cover crop season	FA	150.08	152.20
	RY	126.26	166.90
2021 Soybean season	FA	165.64	92.60
	RY	255.25	267.30
2021 Cover crop season	FA	164.90	142.70
	RY	224.70	158.70
Total cumulation	FA	712.36	530.30
	RY	941.38	893.20

3.5. Global Warming Potential

The net GWP of different cropping systems was assessed and analyzed based on the GWP of N_2O and net CO_2 retention for the period from 2020 to 2021 (Table 6). The simulated N_2O GWP for FA and RY were 20.6% and 2.3% lower, respectively, compared to field observation. Moreover, RY exhibited a higher N_2O GWP than FA, with observed values showing a 35.9% increase and simulated values a 67.2% increase. For net CO_2 retention, the observed value for FA and RY were −7895.25 and −2833.60 kg CO_2 eq ha^{-1} year^{-1}, whereas the simulated values were 168.82 and 901.60 kg CO_2 eq ha^{-1} year^{-1}. Based on field observation, the net GWP for FA and RY were 8057.58 and 3054.14 kg CO_2 eq ha^{-1} year^{-1}. However, the model simulated minus net GWP values for both FA (−39.96 kg CO_2 eq ha^{-1} year^{-1}) and RY (−686.07 kg CO_2 eq ha^{-1} year^{-1}).

Table 6. Observed and simulated global warming potential (GWP) under different cropping systems during the 2020 and 2021 cropping year. FA: fallow; RY: rye; ΔSOC: change of soil organic carbon stock.

Variable	Treatment	Observed	Simulated
		kg C ha^{-1} year^{-1}	
N_2O GWP	FA	162.33	128.86
	RY	220.53	215.52
ΔSOC	FA	-7895.25	168.82
	RY	-2833.60	901.60
Net GWP	FA	8057.58	-39.96
	RY	3054.14	-686.07

4. Discussion

4.1. Simulation of Soil Temperature, Water-Filled Pore Space and Crop Growth

Soil temperature and WFPS are vital factors influencing crop growth [43,44]. Simultaneously, those significantly affect N_2O emissions and the decomposition or sequestration of SOC [45,46]. Thus, accurate estimation of soil temperature and WFPS by the DNDC-Rice model is a critical prerequisite for reliably simulating N_2O emissions and SOC stock dynamics. In some versions of the DNDC model, soil surface temperature is assumed to be equal to the daily average air temperature, as the soil temperature profile is calculated based on a heat flux model [22,36]. In contrast, DNDC-Rice integrates a micrometeorological model, enhancing the accuracy of soil temperature profile estimation [29]. Our study findings indicate that DNDC-Rice effectively simulated the soil temperature (0-5 cm) in both FA and RY system, achieving a nRMSE below 12%, which is comparable to or better than results reported in previous studies for upland cropping systems [47,48]. In our study, the simulated WFPS successfully captured the temporal trends of the observed WFPS, consistent with previous findings [48,49]. However, discrepancies were noted in the dynamic values between the observed and simulated WFPS. The observed WFPS was measured manually on gas sampling days, making it susceptible to human error and limited by discontinuous observation periods. The non-continuous observation may have overlooked critical rainfall or drought events, potentially missing the peaks and troughs in WFPS dynamics. Unlike the observed WFPS, which represents point measurements, the simulated WFPS is continuous, calculated at daily time steps, and represents site-averaged values [50,51]. Therefore, owing to the influence of soil heterogeneity, the simulated WFPS values may not align with the observed values. Additionally, a previous study reported that the DNDC-Rice model overestimated water loss through evapotranspiration [52], resulting in an underestimation of soil water content, which is consistent with our results.

Several studies conducted in rice systems have reported that DNDC-Rice tends to overestimate rice straw biomass [52,53]. Similarly, our findings showed that simulated biomass and yield of soybean were higher than the observed values. The crop growth sub-model of DNDC-Rice integrates a crop carbon metabolism model, resulting in simulated crop growth being influenced by nitrogen availability and carbon allocation [29]. The DNDC-Rice model incorporates specific growth functions, calibrated for different rice varieties, to simulate rice growth [31], while it still lacks specific growth functions for other dryland crops, such as soybean and rye. In the empirical crop growth sub-model, plant growth and the allocation ratio of absorbed nitrogen (N) are calculated based on TDD, while N uptake is regulated by TDD and the availability of soil N. It is well established that soybean is capable of absorbing and transporting substantial amounts of N through biological N fixation, providing N for utilization by all parts of the plant [54] and nitrogen fixation is, of course, assumed in DNDC-Rice. Nitrogen fixation rate can be set for each crop as a constant in DNDC-Rice. However, it doesn't vary with environmental factors and crop growth. In field conditions, nitrogen fixation increases or decreases as rhizobia increase or decrease, but DNDC-Rice does not predict such temporal variability. Due to the absence of accurate simulation of biological nitrogen fixation in soybean, the DNDC-Rice model may inaccurately estimate nitrogen uptake, leading to incorrect simulations of soybean biomass and yield. Therefore, it is essential to develop and calibrate the relevant modules to improve the DNDC-Rice model.

4.2. Simulation of Greenhouse Gas Emission and Soil Organic Carbon Stock

While the trend of daily CO_2 flux simulated by the DNDC-Rice model was similar to the observed data, both the daily fluxes and cumulative fluxes were overestimated. Due to the physical disturbance of the soil surface, tillage events often produce a temporary burst of soil CO_2 emission [55]. Following tillage, the DNDC-Rice model exhibited an immediate response, rapidly increasing the simulated daily soil CO_2 flux (Figure 5). In the model, daily CO_2 flux is regulated by the tillage factor. To prevent an excessive increase in CO_2 emissions induced by tillage, this study reduced the tillage factor in the model. In contrast, the observed daily CO_2 flux during the same period showed

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no significant changes, possibly due to the limitations of discontinuous field sampling, which may have failed to capture the emission peaks induced by tillage events. Consequently, for a period following the tillage event, the simulated daily soil CO_2 emissions were always higher than the observed values. Soil respiration is divided into autotrophic respiration, primarily driven by plant roots, and heterotrophic respiration, which is mainly driven by microorganisms [56]. In this study, the DNDC-Rice model overestimated soybean biomass, which is associated with a well-developed underground root system. Furthermore, the biomass distribution among various organs during crop growth simulation is determined by the ratios of grain, shoot, and root specified in the crop parameter settings of the DNDC-Rice model. An excessively high root allocation ratio may result in an overestimation of the simulated root biomass. This likely led to an overestimation of root autotrophic respiration during the simulation, resulting in an excessively high CO_2 flux. Another main source for the soil CO_2 flux is the soil heterotrophic respiration, which is linked to the sequestration and decomposition of SOC [57]. In the field experiment, both autotrophic and heterotrophic respiration of soil occurred throughout the cover crop season (from November to June) in both the FA and RY systems. Compared to natural weeds in the FA system, the cultivation of cover crops within the RY system contributed to a higher root biomass, thereby enhancing soil autotrophic respiration and resulting in higher CO_2 emissions. In DNDC-Rice, weeding dates and the degree of weed growth can be set in three levels (no, moderate, and serious), but we did not set it. Instead, weed biomass input was set as green manure input to reproduce accurate carbon input. The absence of weed growth process would cause the poor accuracy of soil autotrophic respiration during the cover crop season in the FA system. As a result, the simulated CO_2 emissions for the cover crop season in the FA system were lower than the observed values, thereby exacerbating the discrepancy in CO_2 emissions estimation between the FA and RY systems in estimation. Therefore, it must be crucial to improve the accuracy of weed growth process CO_2 emission

Some studies have documented that cover crops have the potential to enhance SOC stocks [58,59]. The biomass carbon from cover crop residues supplies nutrients and energy to soil microorganisms, a portion of which is subsequently converted into microbial carbon, thereby contributing to an increase in SOC stocks and enhancing carbon sequestration [60]. The observed SOC stock in the RY system was higher than that in the FA system, and the DNDC-Rice model reproduced these results, although the discrepancy was amplified. These results demonstrate the DNDC-Rice model's capability to accurately simulate the cover crop-induced SOC enhancement. The amplified difference between the FA and RY systems may also be attributed to the absence of natural weed growth calculation mentioned above, which prevented the DNDC-Rice model from accurately simulating the contribution of weed biomass to the soil carbon pool in the FA system. Overall, the simulated variation in SOC stock closely followed the observed trend over the period from 2008 to 2021. However, the model could not reproduce the interannual variability observed in the field. In the DNDC model, SOC is automatically allocated to litter, labile humus (humad), and recalcitrant humus pools in fixed proportion [36], and this same algorithm is also employed in the DNDC-Rice model. However, whether the proportion set within the model aligns with the observed data remains uncertain, as we did not conduct a carbon composition analysis of the field soil. We speculate that inconsistent allocation proportion and pathways of SOC may be one of the factors contributing to the discrepancies between the model simulations and field observations. Moreover, in DNDC-Rice, SOC stock was calculated on a daily time step using predefined equations. During the estimation process, the soil bulk density remained consistently aligned with the initial settings. In contrast, observed data were gained through manual sampling and measurement at fixed annual time points, which may introduce considerable sampling errors and increase uncertainty.

In the present study, DNDC-Rice model effectively reproduced the cover crop-induced divergence in N_2O emissions (FA < RY). The reproduction of elevated N_2O emissions in RY systems likely reflects model's effective parameterization of cover crop decomposition dynamics, particularly the enhanced denitrification potential from increased biomass carbon and soil moisture retention. Although the DNDC-Rice model effectively captured the seasonal variation in N_2O fluxes, it

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significantly underestimated the cumulative fluxes. N_2O emissions from soil are commonly released into the atmosphere in a pulsed manner [61], with peak emissions persisting for no more than a few weeks [62]. Meanwhile, in cropping systems, peak N_2O emission events typically account for 50–90% of the annual emissions [63,64]. However, previous studies have identified limitations in the DNDC-Rice model, which fails to accurately predict the timing and magnitude of high N_2O emission pulses [52]. Our findings showed that the simulated daily N_2O fluxes were lower than the observed values during peak N_2O emission events, leading to an underestimation of cumulative N_2O fluxes. Additionally, we observed that the periods of underestimation in daily N_2O fluxes roughly coincided with those of underestimation in WFPS. WFPS is a key driver in the model's simulation of nitrification and denitrification processes, with a profound impact on the prediction of N_2O emissions [65]. Therefore, the discrepancy between the simulated daily N_2O fluxes and observed values is likely due to the underestimation of WFPS. Therefore, improving the accuracy of WFPS simulations, as well as modifying the equations governing soil nitrogen dynamics to better simulate N_2O emission pulse events, will be key directions for enhancing the DNDC-Rice model's accuracy in predicting N_2O emissions.

Net GWP is derived from the GWP of N_2O and changes in SOC stock in this study and the substantial interannual variability in observed SOC values also contributes to unavoidable errors in net GWP calculations. Field observations indicated a reduction in SOC stock during the period from 2019 to 2021. In contrast, the DNDC-Rice model, which fits a time-dependent curve for SOC stock based on long-term observational data (2008-2021), simulated an increase in SOC stock during the 2019-2021 period, contradicting the observed results. This inconsistent SOC variation resulted in a discrepancy between the observed and simulated net GWP values. Given the noticeable interannual variation in the observed SOC stock, comparing the observed and simulated net GWP over longer time intervals would be more reasonable.

5. Conclusions

This study conducted a field validation of the DNDC-Rice model using data on crop productivity, soil parameters, and GHG fluxes from a soybean system incorporating two cover crop management practices, to evaluate its simulation performance within the context of an upland cropping system. The model accurately simulated soil temperature, but it underestimated WFPS and N_2O emissions. In contrast, the simulated values for CO_2 emissions, soybean biomass, and yield were overestimated. While the model successfully captured the long-term variation in SOC stock, the annual SOC values were frequently either underestimated or overestimated. Moreover, the DNDC-Rice model could reproduce the differences between RY and FA in terms of crop yield, GHG emissions and SOC stock, although these differences may be exaggerated or diminished due to discrepancies between the simulated and observed values. These findings indicated that further refinements are needed to improve the model's accuracy in estimation. Due to algorithmic limitations, the model failed to accurately simulate the growth of soybean and N_2O emission pulse events. Therefore, the crop growth sub-model for upland systems and the N dynamics equations in the DNDC-Rice model required further refinement.

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