Modelling methane emissions and grain yields for a double-rice system in Southern China with DAYCENT and DNDC models

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Abstract

Methane (CH_4) is an important greenhouse gas (GHG) that contributes to climate change and one of its major sources is rice cultivation. The main aim of this paper was to compare two well-established biogeochemical models, namely Daily Century (DAYCENT) and DeNitrification-DeComposition (DNDC) for estimating CH_4 emissions and grain yields for a double-rice cropping system with tillage practice and/or stubble incorporation in the winter fallow season in Southern China. Both models were calibrated and validated using field measured data from November 2008 to November 2014. The calibrated models performed effectively in estimating the daily CH_4 emission pattern (correlation coefficient, r = 58−63, $p < 0.001$), but model efficiency (EF) values were higher in stubble incorporation treatments, with and without winter tillage (treatments S and WS) (EF = 0.22−0.28) than that in winter tillage without stubble incorporation treatment (W) (EF = −0.06−0.08). We recommend that algorithms for the impacts of tillage practice on CH_4 emission should be improved for both models. DAYCENT and DNDC also estimated rice yields for all treatments without a significant bias. Our results showed that tillage practice in the winter fallow season (treatments WS and W) significantly decreased annual CH_4 emissions, by 13−37% ($p < 0.05$) for measured values, 15−20% ($p < 0.05$) for DAYCENT-simulated values, and 12−32% ($p < 0.05$) for DNDC-simulated values, respectively, compared to no-till practice (treatments S), but had no significant impact on grain yields.

Keywords: Methane; Management practices; DAYCENT model; DNDC model; Double-rice cropping system; China

1. Introduction

Methane (CH_4) is a powerful greenhouse gas (GHG), the atmosphere amount of which has more than doubled since pre-industrial times, and approximately 60% of CH_4 originates from anthropogenic sources (Nisbet et al., 2019; UNEP and CCAC, 2021). Rice paddy fields are a major source of CH_4 emissions, which are responsible for 8−11% (5−38 Tg CH_4 yr^{-1}) of global anthropogenic CH_4 emissions (Shukla et al., 2019; Saunois et al., 2020). Quantification of CH_4 emissions from rice paddy soils is necessary for developing mitigation options and policies. However, accurate estimation of CH_4 emissions is a great challenge due to the time consuming and expensive field flux measurements. Consequently, process-based models for estimating CH_4 emissions have been developed to complement physical experiments by employing computers to calculate the likely outcomes of different physical phenomena (Giltrap et al., 2010).

Simulation models allow complex interactions and real-world problems to be examined in a cost- and time-effective way (Giltrap et al., 2010; Cheng et al., 2013). DAYCENT and DeNitrification-DeComposition (DNDC) are two popular ecological process-based models to simulate methane (CH_4) emissions from rice paddy fields in China (Li et al., 2006; Cheng et al., 2014; Zhang et al., 2019; Wang et al., 2021). Cheng et al. (2013) developed and evaluated the DAYCENT CH_4 module using total 97 rice paddy sites across China, with an overall *r* of 0.83 for model predictions *vs.* measurements. In addition, the DNDC model has been corroborated by many CH_4 emission datasets from Chinese rice fields, and the simulated values are generally in good agreement with the observed CH_4 field emissions (Zhang et al., 2002; Li et al., 2006; Zhang et al., 2019; Zhao et al., 2020; Wang et al., 2021).

China is the largest rice producer in the world and is also trying to increase rice grain yield by improving rice cultivation management, while at the same time, minimizing CH_4 emissions from rice paddy. Rice is a one of the primary cereal crops in China, with an area of about 30 million ha (FAO, 2020). Double rice is the common cropping system in China, accounting for >40% of the total harvested area and emitting about 50% of the total CH_4 emission from rice paddy fields in China (Zhang et al., 2011; Chen et al., 2013). The double rice cropping system typically consists of one winter fallow season, and two rice growing seasons each year. Considerable research has been conducted on improving field management in the double-rice cropping system to mitigate CH_4 emissions while maintaining optimal rice yields. These have mainly focused on the fertilization rate and method (Tang et al., 2020; Fu et al., 2021; Wang H. et al., 2021), irrigation management method (Li et al., 2020; Zeng and Li, 2020), and tillage management (Chen et al., 2021; Wang X. et al., 2021).

Tillage after rice harvest in the winter fallow season can play key role in CH_4 emissions. It is beneficial for rainwater to run through into the subsoil, and thus reduce rainwater accumulation in the winter fallow season. Consequently, it would directly reduce CH_4 emission during off-rice season because of a less anaerobic environment in the topsoil (Zhang et al., 2016). Moreover, it could also indirectly inhibit CH_4 emissions during the following rice growth seasons. For example, tillage incorporates rice residues into the soil during winter fallow season, and soil microorganisms accelerate the decomposition of organic matter and thereby facilitate CH_4 production and emissions (Pandey et al., 2012; Hussain et al., 2015). Subsequently, it would reduce the carbon substrate for methanogenesis during the following rice seasons, and thus decrease CH_4 emissions (Yang et al., 2018).

As a representative region of the double-rice cropping system, Jiangxi Province has the largest rice area; about 11% of total rice area in China (Yearbook, 2014) and emits substantial quantities of CH_4. However, to the best of our knowledge, the process-based DNDC and DAYCENT models have not previously been calibrated and evaluated for a double-rice cropping system with different management in the winter fallow season in China. Moreover, little research has been done to compare different process-based models in simulating CH_4 emissions. Therefore, the main objective of this study was to compare the results from two well-established biogeochemical models (DAYCENT and DNDC) for estimating CH_4 emissions and crop yields from a double rice system in Jiangxi Province, southeast China from November 2008 to November 2014 under three different managements in the winter fallow season. This study will improve process understanding and enhance further applicability of DAYCENT and DNDC models for predicting CH_4 emissions from the Chinese paddy rice ecosystem.

2. Materials and Methods

2.1. Experimental site and treatments

This field experiment was conducted at Yingtan City, Jiangxi Province, China (28°15'N, 116°55'E) for 6 years from November 2008 to November 2014. This region is a typical double-rice cropping cultivation area, with one winter fallow season and two rice growing seasons each year. The selected soil is classified as a typical Haplaquept (18.2% clay, 31.3% silt, 50.5% sand), with its initial properties as follow: SOC 16.2 g kg^{-1}, soil total nitrogen 1.43 g kg^{-1}, bulk density 1.12 g cm^{-3}, pH (H_2O) 4.74. The detailed site description and soil parameters were reported by Yang et al. (2018). The daily air temperature (°C) and precipitation (mm) were collected from weather station at the study site (Fig. S1). The average annual temperature and total precipitation were 18.2°C and 194.2 cm, respectively. The monthly mean air temperature and rainfall from 2008 and 2014 at the field site are presented in Table S1.

Compared with rice stubble incorporation during the rice season, applying rice stubble during the fallow season produces much lower CH_4 emissions (Yan et al., 2009). Additionally, soil tillage with rice stubble incorporation in the winter fallow season has been reported to reduce CH_4 emission relative to rice stubble incorporation just before rice transplanting (Zhang et al., 2016; Yang et al., 2018). In this study, three treatments were laid out in the winter fallow season with three replicates in a fully randomized block design: rice stubble incorporation without winter tillage (S), winter tillage with rice stubble incorporation (WS), and winter tillage without rice stubble incorporation (W). Fresh rice stubble was left standing in the fields after late rice harvest in treatments S and WS, with a dry weight of 2.5−4.0 t ha^{-1} (about 30 cm long), while stubble was moved out of field after late rice harvest in treatment W. No extra straw/stubble was incorporated in the following rice seasons.

Generally, ploughing is the traditional tillage practice in the local area, with tillage occurring before the transplantation of early- and late-rice. For better cultivation, all experimental plots (S, WS and W) were ploughed before the transplantation of early- and late-rice rice without any rice stubble/straw incorporation. The winter tillage plots (treatments WS and W) were ploughed again as soon as the late rice had been harvested. The tillage operation (up to 20 cm soil depth) was the same for all tillage practices.

Local rice cultivars, Zhongzao 33 and Nongxiang 98, were planted in the following early-rice and late-rice seasons, respectively. Seeds were sown in the seeding nursery and then transplanted to the experimental plots at the third and fourth leaf stage. The early rice seedlings were transplanted in middle or late April and harvested in middle or late July, and then late rice seedlings were transplanted immediately after the early rice harvest and harvested in November or December from 2009 and 2014 (Table 1). For each rice season, the total amount of nitrogen (N) and potassium (K) fertilizers applied were 180 kg N ha^{-1} and 150 kg K ha^{-1}, respectively. These fertilizers were applied at three different times as basal, tillering and panicle initiation fertilizer with a ratio of 5:3:2 and 3:4:3, respectively. Phosphorus (P) fertilizer was applied as a basal fertilizer at a rate of 75 kg P ha^{-1}.

For water management, flooding was initiated 2-4 days before early-rice transplanting, drained after tillering fertilization application for 5-8 days midseason aeration, re-flooded for two or three weeks, then subjected to drying-wetting alternation (with a cycle of 5-day drying and 5 day-wetting) until roughly 1-2 weeks of a dry period before early rice harvest. During the late-rice season, the water management was similar to that during the early-rice season but the duration of the dry period before late rice harvest was roughly 3-5 weeks. A detailed schedule of the field management, including soil tillage, rice cultivation and water management, is presented in Table 1.

2.2. Field measurements and GHG emissions

The CH_4 fluxes were measured using a static chamber (Ma et al., 2009), every 2 to 6 days over the rice seasons, and every 7 to 10 days over the winter fallow seasons in 15 min intervals. The yield of early- and late-rice grain was determined at harvest in each plot by subtracting a moisture content of 0.14 g H_2O g^{-1} fresh weight. The details of measurement information for daily CH_4 flux and yield were described by Yang et al. (2018).

GHG emissions (kg CO_2-eq ha^{-1} yr^{-1}) based on CH_4 emission were estimated using global warming potential (GWP) (CO_2-eq) for CH_4 over a 100-year time span (Eq (1)). The GWP for CH_4 is 28 over a 100-year time span (IPCC, 2021):

$$GHG_{CH4} = 28 \times CH_4 \quad (1)$$

To determine the emission intensity of production, GHG emission per unit of crop yield was calculated (Eq (2)):

$$\text{yield-scaled GHG} = \text{GHG} / (\text{early rice yield} + \text{late rice yield}) \quad (2)$$

2.3. Model descriptions and simulations

We used two process-based ecosystem models, DAYCENT and DNDC, developed to simulate soil carbon and nitrogen dynamic in plant-soil system (Parton et al., 1998; Li, 2000; Gilhespy et al., 2014). Model concept and mechanisms are described in greater detail elsewhere for DAYCENT (Del Grosso et al., 2001; Cheng et al., 2013; Begum et al., 2019), and DNDC (Li et al., 1994; Li et al., 2006). Daily weather data, plant, soil and management data including N fertilizer, water management and tillage are needed as inputs for both models.

With an understanding of the processes of CH_4 production, oxidation and emission, a methanogenesis sub-model for the DAYCENT model was developed for predicting methane fluxes dynamics in rice paddy soils by Cheng et al. (2013). Rice-DAYCENT simulates plant production, soil organic matter (SOM) decomposition, soil hydrology and thermal regimes. The methanogenesis sub-model simulates CH_4 emissions based on methanogenic substrate derived from SOM decomposition and root rhizodeposition, and associated influences of redox potential (Eh) and soil temperature (Huang et al., 1998; Cheng et al., 2013). As described in Cheng et al. (2013), the decomposition of organic matter in soil was simulated by DAYCENT model through heterotrophic respiration using three kinetically defined active, slow and passive pools. The amount of carbon added to the soil through rhizodeposition was simulated using a simplified linear equation with root carbon production estimated in the plant production sub-model. The influence of Eh was simulated under flooding and drainage, respectively. Only part of the CH_4 produced in the process of methanogenesis is emitted to atmosphere because about 40-90% of CH_4 is oxidized to CO_2 by methanotrophs at aerobic-anaerobic interfaces (Huang et al., 1998; Chen et al., 2013). The pathway of CH_4 from the paddy soil into the atmosphere occurs in various ways: *via* aerenchyma in the plant (90%), *via* ebullition (10%) or *via* diffusion through the soil and water layer (1%) (Groot et al., 2003). The methanogenesis sub-model adopted the approach proposed by Huang et al. (2008, 2004) to simulate CH_4 emissions through the rice plant and ebullition. The simulation of CH_4 emission rates through the rice plant was based on the CH_4 production rate, and the fraction of CH_4 emitted *via* rice. The algorithm for simulating CH_4 emissions through ebullition was based on CH_4 production rate, soil temperature, and root biomass. The CH_4 oxidation model was based on field capacity, bulk density, soil temperature, water-filled pore space and volumetric soil water content.

The DNDC model was modified by adding a series of anaerobic process for simulating the carbon cycle and CH_4 emission in rice paddy field as described in Li et al. (2000; 2004). The DNDC model accommodates two components. The first component consists of three main sub-models as follow: the soil climate sub-model calculating soil temperature, moisture and Eh profiles; the plant growth sub-model simulating crop biomass accumulation and partitioning; the decomposition sub-model simulating concentration of substrates, i.e., dissolved organic carbon and NH_4^+, nitrogen oxides. The second component, namely the fermentation sub-model, predicts the CH_4 fluxes dynamics from plant-soil systems. For example, CH_4 production rate was simulated using kinetical equations based on available carbon concentration and temperature as soon as the simulated Eh reaches −150 mV or lower. In addition, CH_4 oxidation rate was simulated using a function of soil CH_4 concentration and Eh. DNDC models simulated CH_4 emissions through plant aerenchyma and ebullition, respectively, based on CH_4 concentration, soil temperature and soil porosity.

2.4. Model calibrations and sensitivity analyses

This study investigated the suitability of the DAYCENT and DNDC models for estimating CH_4, crop yield for typical double rice paddy field in Southern China. This double rice cropping system in our study consists of a 4- or 5-month long winter fallow season, followed by early rice (grown from April to July), and then late rice planted immediately after the early rice harvest (grown from July to November/December). The DAYCENT model was calibrated on crop yield / annual

CH_4 emissions for the site using the measured data from the control treatment S. Model calibration for crop yield / annual CH_4 emissions was done by optimizing the crop parameters of radiation use efficiency (PRDX), optimum temperature (PPDF(1)), and the fraction of CO_2 from soil respiration used to produce CH_4 (Table 2), as suggested by previous studies (Cheng et al., 2014; Begum et al., 2019). The parameter values were modified until the DAYCENT model matched measured grain yield/annual CH_4 emission values from the control treatment S. The calibrated model was then used to run those for another two treatments WS and W from November 2008 to November 2014.

Similarly, the DNDC model was also calibrated on crop yield/annual CH_4 emissions for the site using the measured data from the control with treatment S. Model calibration for crop yields and CH_4 emissions was done by optimizing a combination of different crop growth parameters, including maximum biomass production, biomass fraction, biomass C/N ratio, thermal degree days (Table 3), as suggested by Zhang et al. (2019) and Abdalla et al. (2020). Crop parameter input default values were tested until the DNDC model matched the measured grain yield/annual CH_4 emission values from the control treatment S. The calibrated model was then used to run those for another two treatments WS and W from November 2008 to November 2014.

The sensitivity of DAYCENT and DNDC and the attribution of CH_4 and early-/late-rice grain yields to different input parameters were investigated to quantify the effects of these parameters on the CH_4 emissions and grain yields (Smith and Smith, 2007; Cheng et al., 2013; Wang et al., 2021). The baseline scenario was composed based on the treatment S. Only one parameter was changed at a time and all the other kept constant. Simulations were run to assess how CH_4 and grain yields were affected by average daily temperature (increased/decreased by a range from −2 ^{o}C to +2 ^{o}C), initial SOC content (decreased/increased by a rang from −50% to +50%), soil pH (decreased/increased by a range from −1 to +1) and the amounts of N fertilizer (decreased/increased by a rang from −50% to +50%).

2.5. Statistical methods

The models were validated by comparing measured and simulated values. Based on the statistical routines provide in MODEVAL (Smith et al., 1997; Smith & Smith, 2007), the total difference between measured and simulated values was assessed by calculating the root mean square error (RMSE, Eq. (3)), relative RMSE (rRMSE, Eq (4)), relative deviation (RD, Eq(5)):

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(Si-Mi)^2}{n}} \qquad (3)$$

$$\mathrm{rRMSE} = \frac{\mathrm{RMSE}}{\overline{\mathrm{M}}} \times 100 \qquad (4)$$

$$\mathrm{RD} = \frac{M_i - S_i}{M_i} \times 100 \qquad (5)$$

Where *Si* is the simulated value, *Mi* is the measured value, n is the number of measured values, and $\overline{\mathrm{M}}$ is the average of the measured values. The rRMSE can compare between different models whose errors are measured in the different units, and a low rRMSE often indicates a strong predictive power.

The DAYCENT and DNDC models’ accuracies were evaluated by calculating modelling efficiency (EF, Eq (6)). EF provides a comparison of the efficiency of the chosen model compared to describing the data as the mean of the measurements (Yang et al., 2014):

$$EF = 1 - \frac{\sum_{i=1}^{n}(Si - Mi)^2}{\sum_{i=1}^{n}(Mi - \bar{M})^2} \quad (6)$$

Values of EF can be positive or negative values. Specifically, a positive value shows that the simulated values describe the trend in the measured data better than the mean of the measurements, and closer to 1 suggests a better modelling efficiency. A negative value indicates that the simulated values describe the data less well than a mean of the measurements.

The sample correlation coefficient (r) was used (Eq. (7)) to test for association between the simulated and measured values (Smith et al., 1997).

$$r = \frac{\sum_{i=1}^{n}(M_i - \bar{M})(S_i - \bar{S})}{\sqrt{[\sum_{i=1}^{n}(M_i - \bar{M})^2]}\sqrt{[\sum_{i=1}^{n}(S_i - \bar{S})^2]}} \quad (7)$$

All the statistical analyses were conducted in R version 3.4.0 (Team, 2008) and Minitab (Minitab, Limited Liability Company, USA), and a Map was created using Original (Origin Lab Corporation, USA).

3. Results

3.1. Models calibration and sensitivity analyses

The DAYCENT and DNDC models were calibrated by adjusting the combination of crop parameters as shown in Tables 2 and 3 to enhance their performances in simulating CH_4 emissions and grain yields. The calibrated DAYCENT and DNDC model accurately simulated the measured annual CH_4 emissions, early and late rice yields for the control with treatment S from November 2008 to November 2014 (Table 4).

The sensitivity of the DAYCENT- and DNDC-models to the essential input parameters (i.e. SOC content, soil pH, the N fertilizer rate and air temperature) for simulating annual CH_4 emission and grain yield of double-cropping rice system was tested. As shown in Fig. 1, DAYCENT was more sensitive to changes in SOC content and soil pH than the other parameters, whilst the DNDC was more sensitive to changes in air temperature and N fertilizer. For grain yields, neither model was sensitive to change in air temperature, but DNDC was very sensitive to changes in N fertilizer rate and SOC content (Fig. 1).

3.2. Performance of DAYCENT and DNDC models in simulating CH_4 emissions and rice grain yields

3.2.1. CH_4 emissions

Fig. 2 shows that, for all treatments, DAYCENT- and DNDC-simulated daily CH_4 emissions pattern were generally consistent with the measured CH_4 flux dynamics. The daily CH_4 emissions for all three treatments increased under continuous flooding, with the highest peak measured at about 3−5 weeks after the early-rice transplanting and 2−4 weeks after late-rice transplanting. Thereafter, daily CH_4 emissions dramatically decreased after midseason aeration. An emission peak occurred again after re-flooding, particularly in the early-rice season. CH_4 emissions always showed a lower peak in the treatment W, observed both in simulations and measurements. As shown in Table 5, DAYCENT and DNDC models performed better when simulating treatments S and WS, with a lower rRMSE (i.e., 124−129) and higher EF values (i.e., 0.22−0.28), than treatment W (i.e., 140-150 and −0.07−0.08, respectively), but all three treatments showed significant correlations of simulated versus measured daily emission values ($r = 58\text{-}63$, $p < 0.001$).

The annual CH_4 emissions simulated by DAYCENT and DNDC models were also generally similar to the measured annual values for all three treatments (Table 4).

The measured average annual CH_4 emissions were 175, 152, and 111 kg C ha^{-1} for the treatment S, WS and W, respectively (Table 4). Correspondingly, the DAYCENT- and DNDC-simulated average annual CH_4 emissions were 173, 148 and 138 kg C ha^{-1}, and 173, 153 and 117 kg C ha^{-1}, respectively. Both the observed and simulated results showed significantly lower ($p < 0.05$) annual CH_4 emissions from the treatment W than from the treatment S. Over the six annual rotation cycles from November 2008 to November 2014, the measured annual CH_4 emission was not significantly different within years for treatment S, while significantly decreased from the first rotation year of 2008-2009 to final rotation year of 2013-2014 for treatments WS and W (Fig.3).

As shown in Fig.4, winter tillage (treatments WS and W) decreased the seasonal CH_4 emission for early rice season from −36 to −15% for measured values ($p<0.05$), from −26 to −17% for DAYCENT-simulated values, and from −38 to −13% for DNDC-simulated values. Similarly, the seasonal CH_4 emissions for late rice season also decreased from −40 to −14% for measured values, from −18 to −14% for DAYCENT-simulated values, and from −28 to −11% for DNDC-simulated values. By contrast, the tillage in winter fallow season (treatments WS and W) increased the seasonal CH_4 emission by 31−87% for measured values ($p<0.05$) and 9−36% for DAYCENT-simulated ($p < 0.05$) compared to no-till treatment (treatment S).

3.2.2. Rice yields

The DAYCENT and DNDC models estimated grain yield for all treatments effectively (Table 4). As shown in Fig. 5, the correlation coefficient (r) of simulated against measured yields of both early and late rice season were 0.90, 0.85 and 0.92 by DAYCENT model ($p < 0.001$), which were higher than the values of 0.82 ($p < 0.01$), 0.67 ($p < 0.05$) and 0.58 by the DNDC model, for treatments S, WS and S, respectively.

On average, the measured yields were 6.3, 6.6, and 6.5 t ha^{-1} over early rice, and 6.4, 6.5, and 6.3 t ha^{-1} over late rice, for the treatments S, WS and W, respectively (Table 4). Correspondingly, the DAYCENT-simulated average yields were 6.4, 6.4, and 6.4 t ha^{-1} over early rice, and 6.3, 6.3, and 6.3 t ha^{-1} over late rice; DNDC-simulated average yields were 6.1, 6.7, and 7.0 t ha^{-1} over early rice, and 6.6, 6.8, and 6.7 t ha^{-1} over late rice, respectively. Overall, the grain yields were not significantly different among the three treatments, observed both in measurements and simulations (Table 4).

Over the six annual rotation cycles from November 2008 to November 2014, the annual yields were not significantly different within most years, except in the rotation year of 2009-2010. The lower annual yield in 2010 was due to the flood damage, resulting in the delaying of late rice transplanting, thus reducing the rice grain yields (Fig.3).

3.2.3. Yield-scaled GHG emissions

Compared with the treatment S, measured yield-scaled GHG emissions were lower by 17% for treatment WS and by 38% for treatment W ($p < 0.01$) (Table 3). Similarly, simulated yield-scaled GHG emissions were lower by 15% and 16% with treatment WS, by 21% and 37% with treatment W ($p < 0.01$) for DAYCENT and DNDC, respectively.

4. Discussion

4.1. Model calibration and sensitivity analysis

In this study, calibration and validation of DAYCENT and DNDC models was required because of differences in the Chinese rice cultivars and climates (Cheng et al., 2013; Wang et al., 2021). However, the adopted parameters for calibration between DAYCENT and DNDC models are different due to differences in the crop growth and CH_4 algorithms in the two models (Li, 2000; Cheng et al., 2013).

Sensitivity analysis was also used to evaluate the response of the simulated results to the variation in the input parameters. We utilized the calibrated DAYCENT and DNDC models to test how CH_4 emission and rice grain yield were influenced by soil properties, climate factors and N fertilizer application rates. As the CH_4 algorithm is implemented in different ways, the results indicate the robustness and uncertainty of the different processes. While the models showed good performances on aerobic systems, impacts of management changes and mitigation strategies, the diverse management on the considered sites will allow the models to be challenged on these aspects as well. For both of CH_4 emission and grain yields, DAYCENT and DNDC models were not sensitive to the same parameters as shown in Fig. 1, which may be due to differences in the algorithms of the methanogenesis sub-model (Li, 2000; Cheng et al., 2013), thus resulting in the differences of dominant factors influencing CH_4 emissions, with the effects of other factors being overshadowed by the influence of the dominant factors (Wang et al., 2021).

For simulating CH_4 emissions, the DAYCENT model is more sensitive to changes in initial SOC content. The initial SOC content determined the amount of carbon substrate for methanogenic bacteria, for CH_4 production and also emissions (Conrad, 2007). Therefore, annual CH_4 emissions changed with a change in the initial SOC content in the same direction under otherwise identical conditions (Fig. 1). By contrast, the DNDC model was less sensitive to the changes of initial SOC content (Fig. 1), which was also reported by Wang et al. (2021). This can be explained by differences in the calculation of available C from SOM decomposition between the two process models. Moreover, DAYCENT and DNDC models have a different way of representing initial SOC. For example, the initial SOC stock (g m^{-2}) at 20 cm soil depth was required to define the initial soil organic matter pools in DAYCENT model, but initial SOC content (kg kg^{-1}) at 10 cm soil depth was required in DNDC model. Therefore, when the same changes of initial SOC content were applied, DAYCENT and DNDC models have different relative changes of initial carbon stock input, thus different changes of available C concentration.

Decreased soil pH (pH < 4.7, under acidic conditions) significantly decreased annual CH_4 emissions in DAYCENT model, but increased pH slightly increased CH_4 emissions, which is related to the soil pH thresholds effecting decomposition rate in the model. When pH value decreases especially from ~5 to 3, the decomposition rate dramatically reduces in the DAYCENT model, thereby significantly decreasing CH_4 emissions. By contrast, when soil pH value increases from 5 to 7, the decomposition rate barely changes because, it is close to the maximum rate in the DAYCENT model. Cheng et al. (2013) also showed that the performance in simulating in CH_4 emission by DAYCENT was mainly controlled by the initial SOC content and soil pH. However, for DNDC, the annual CH_4 emission was not sensitive to the changes of soil pH, but very sensitive to air temperature (Wang et al., 2021). As shown in Li (2000), the effect of temperature on CH_4 production rates in DNDC is based on an exponential function, and when temperature increase, the temperature effect becomes larger directly. Moreover, DNDC simulates CH_4 fluxes diffusion through ebullition to atmosphere using a simplified linear equation with temperature. Therefore, this is probably why a significantly effect of temperature on CH_4 emissions was observed in DNDC model. By contrast, in DAYCENT model, the algorithm for calculating transport CH_4 through ebullition was based on a natural logarithm function with temperature, thus there is barely changes of temperature effects when temperature increase/decrease within 2 ^{o}C (Cheng et al., 2013).

For simulating yields, the DAYCENT model was slightly sensitive to changes of air temperature, which may be due to the saturation effect above 30 ^{o}C for rice paddy in the model. In the test site, the average values of maximum temperature in rice reproductive period were 30.29–34.58 ^{o}C during June to September, therefore the simulated yields only slightly changed with air temperature changes. In contrast, the DNDC model was also slightly sensitive to changes of air temperature, but very sensitive to the changes of N fertilizer rate and initial SOC content. In the plant growth sub model of DNDC, N uptake by crop is the key process linking crop growth, and the availability of NH_4^+ and NO_3^- in soil profile is one of main controlling factors on N uptake rate (Li et al. 1994). Therefore, changes of N fertilizer rate directly affect the concentration of NH_4^+ and NO_3^- in the model, and thereby influence rice plant growth and yields as well. On the other hand, calculating NH_4^+ concentration from N fertilizer in DNDC model is also controlled by the concentration of soluble C from decomposition sub model, which is why changes of initial SOC content in DNDC directly affects the rice plant growth and grain yields (Li et al., 1992).

4.2. Evaluation of DAYCENT and DNDC models

4.2.1. CH_4 emissions

Simulation of substrate C available under different water and field management is crucial for predicting CH_4 emissions accurately by DAYCENT (Cheng et al., 2013) and DNDC (Li, 2007). Large CH_4 emissions were simulated at the middle growth stage in the month of May for early rice, and at the early growth stage in the month of July-August for late rice, when carbohydrates derived from plants was greater, and soil Eh was lower due to continuous flooding conditions after rice transplantation in this study. A clear CH_4 peak was also simulated during the re-flooding period after midseason aeration in the month of May-June for early rice and August-September for late rice. This could be due to re-flooding cutting off the oxygen supply from the air into soil and decreasing soil Eh, thus benefiting methanogenetic activity (Cai et al., 2000). Correspondingly, both the DAYCENT and DNDC models simulated relatively lower soil Eh during re-flooding period after midseason aeration, with on average values of −193, −192 and −190 and −185, −174 and −173 mV for treatment S, WS and W, respectively.

A difference between seasonal simulated and measured CH_4 emissions was observed in this study, especially in the winter fallow season. In the test sites, field plots were fallow in the winter season with soil being undrained after late rice harvest, which were often flooded after rain (Zhang et al., 2016), hence providing favourable anaerobic conditions for CH_4 production. Compared with DNDC model, DAYCENT accurately estimated the seasonal CH_4 emissions during the winter fallow season, mainly due to better simulating the water condition during the winter fallow season. However, the DNDC model runs without setting flooding conditions during the winter fallow season because there is not a suitable corresponding flood setting option in the model, thereby resulting in underestimated seasonal CH_4 emissions during winter fallow season. But the seasonal CH_4 emissions during the winter fallow season contributed, on average, around 2% to the annual CH_4 emissions observed in measured and DAYCENT-simulated values, hence it had small effects on the estimation of annual CH_4 emissions. On the other hand, DNDC underestimated the seasonal CH_4 emissions from early rice seasons while slightly overestimating emissions from late rice seasons for all treatment S, WS and W, which may be due to the sensitivity of the DNDC model to air temperature changes. Slightly lower air temperatures were found in the month of May-June (i.e., 22.9−26.0 ^{o}C) compared to July-September (i.e., 25.6−29.6 ^{o}C) in this study, which also led to a CH_4 emission peak for early and late rice season, respectively.

The response of CH_4 emissions to the incorporation of stubble was influenced by the winter tillage. Winter tillage (treatments WS and W) significantly increased CH_4 emission by 31−87% for measured values during the winter fallow season relative to no winter tillage (treatment S) (Fig. 4), in agreement with previous measurements from a single-cropping rice field in northeast China (Liang et al., 2007). By contrast, it significantly decreased CH_4 emissions during the following early- and late-rice seasons by −36 to −15% (Fig. 4), in agreement with our early field observation (Yang et al., 2017), and previous measurements from a single-cropping rice field in southern Brazil (Bayer et al., 2015).

The impact of winter tillage practices was satisfactorily replicated by both DAYCENT and DNDC models. Compared to no-tillage in the winter fallow season, winter tillage promotes the decomposition of rice stubble, which creates an anaerobic soil environment suitable for methanogenic activity because of oxygen consumption, and thereby enhanced observed/simulated CH_4 emissions in the winter fallow season (Zhang et al., 2015; Yang et al., 2018). By contrast, as the easily decomposable portion of the rice stubble has largely been decomposed during the whole winter fallow season, the positive effect of the remaining rice stubble (a less-decomposable part of organic matter) on CH_4 production and emissions is greatly reduced during the following seasons (Watanabe and Kimura, 1998; Bayer et al., 2015).

4.2.2. Rice yields

An adequate simulation of yield is of key importance to accurately predict CH_4 emissions for process-based models of plant-soil systems because carbohydrate exudation from roots, the major labile carbon source driving CH_4 emissions, is closely related to rice plant biomass (Cheng et al., 2013). Both models simulating rice yields performed effectively after calibration in this study. Significant positive correlations of simulated against measured rice yields were observed in this study, with r values of 0.85−0.92 for DAYCENT, and 0.67−0.82 for DNDC (Fig. 5). Similar previous studies in China were also able to simulate rice yield adequately using the DAYCENT (Stehfest et al., 2007; Cheng et al., 2013) and DNDC models (Zhang et al., 2019; Zhao et al., 2020). It is crucial the key growth processes (i.e. plant production and allocation of net primary production, mineralization/immobilization, and nutrients uptake by plant) are well represented in the approaches of the DAYCENT and DNDC models (Li et al., 1994; Cheng et al., 2013).

Tillage and/or stubble incorporation in winter fallow season did not impact rice yields significantly (Table 4 and Fig. 3). In the DNDC and DAYCENT models, once the soil is ploughed, decomposition rates of soil organic matter would be directly increased due to the changes in soil structure and aeration conditions (Li et al., 1994; Cheng et al., 2013). As for stubble incorporation after harvest, SOM would increase by a certain percentage in DAYCENT and DNDC models. However, changes SOM (i.e. soil C content) would not have a direct effect on simulation of yield, especially in DAYCENT. Moreover, only 15% of leaf and stem was assumed to be left in field after harvest in the DNDC model, which might have less impact on total SOM, and thereby rice yields.

4.2.3. Yield-scaled GHG emissions

Compared with the treatment S, annual CH_4 emissions were clearly lower in the treatments of WS and W, observed in both field measured and simulated results (Table 4). Similar measured results from a single-cropping rice field in northeast China were reported by Liang et al. (2007). Additionally, maintaining rice paddy yield has always been given priority before implementation of alternative management practice (Liu et al., 2016). In this study, no significant differences in rice paddy yields were observed among three treatments over the six years, consequently, annual yield-scaled GHG emissions were lower in the treatments of WS and W compared with treatment S for both model simulated and field measured results (Table 4). Similar findings were shown by Zhang et al. (2016) and Yang et al. (2018). This indicates that the tillage practice in the winter fallow season could be a potential strategy for reducing annual GHG emissions without a significant impact on grain yield in double rice cropping systems.

5. Conclusions

This study has provided an insight into the differences of model performance between DNDC and DAYCENT in simulating CH_4 emission from a double-rice cropping system in Southern China. Both models were able to effectively estimate daily CH_4 emission patterns and grain yields across all treatments from November 2008 to November 2014. Compared with the DNDC model, DAYCENT simulated the seasonal CH_4 emissions during winter fallow seasons better, mainly due to better reflecting the water conditions in the real field for winter fallow seasons. Moreover, the high sensitivity of the DNDC model to air temperature results in imperfectly estimated seasonal CH_4 emissions for early and late rice seasons. As observed in the simulations of both models and field measurements, the tillage practice in the winter fallow season could be a potential strategy for reducing annual CH_4 emissions without a significantly impacting grain yield in double rice cropping systems. Further measurements of emissions for tillage and/or stubble incorporation in the winter fallow season are recommended before implementing the model outcomes.

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.

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Table

Table 1 Schedule of field management practices in the experimental plots over the six years from November 20108 to November 2014.

Season	Field Management	2008-2009	2009-2010	2010-2011	2011-2012	2012-2013	2013-2014
Winter fallow	Winter tillage	8 Nov 2008	13 Nov 2009	2 Dec 2010	3 Nov 2011	5 Dec 2012	11 Nov 2013
Early-rice	Spring tillage	12 Apr 2009	17 Apr 2010	19 Apr 2011	23 Apr 2012	20 Apr 2013	10 Apr 2014
	First flooding	13 Apr 2009	17 Apr 2010	21 Apr 2011	23 Apr 2012	22 Apr 2013	10 Apr 2014
	Basal fertilizers	17 Apr 2009	26 Apr 2010	22 Apr 2011	27 Apr 2012	24 Apr 2013	13 Apr 2014
	Rice translates	17 Apr 2009	27 Apr 2010	23 Apr 2011	27 Apr 2012	24 Apr 2013	13 Apr 2014
	Tillering fertilizers	26 Apr 2009	11 May 2010	14 May 2011	15 May 2012	17 May 2013	29 Apr 2014
	Midseason drainage	8 May 2009~15 May 2009	23 May 2010~27 May 2010	23 May 2011~31 May 2011	25 May 2012~5 Jun 2012	28 May 2013~3 Jun 2013	22 May 2014~29 May 2014
	Second flooding	16 May 2009~2 Jun 2009	28 May 2010~2 Jun 2010	1 Jun 2011~24 Jun 2011	6 Jun 2012~18 Jun 2012	-	30 May 2014~16 Jun 2014
	Panicle initiation fertilizers	26 May 2009	12 Jun 2010	16 Jun 2011	12 Jun 2012	14 Jun 2013	10 Jun 2014
	Dry/wet alternation	3 Jun 2009~3 Jul 2009	22 Jun 2010~15 Jul 2010	25 Jun 2011~3 Jul 2011	19 Jun 2012~23 Jun 2012	-	17 Jun 2014~29 Jun 2014
	Final drainage	4 Jul 2009	16 Jul 2010	4 Jul 2011	24 Jun 2012	4 Jul 2013	30 Jun 2014
	Rice harvest	9 Jul 2009	22 Jul 2010	11 Jul 2011	13 Jul 2012	18 Jul 2013	16 Jul 2014
Late-rice	Tillage	10 Jul 2009	31 Jul 2010	11 Jul 2011	14 Jul 2012	22 Jul 2013	19 Jul 2014
	First flooding	12 Jul 2009	31 Jul 2010	12 Jul 2011	15 Jul 2012	24 Jul 2013	20 Jul 2014
	Basal fertilizers	14 Jul 2009	5 Aug 2010	16 Jul 2011	27 Jul 2012	24 Jul 2013	22 Jul 2014

Rice translates	15 Jul 2009	5 Aug 2010	16 Jul 2011	27 Jul 2012	24 Jul 2013	22 Jul 2014
Tillering fertilizers	29 Jul 2009	23 Aug 2010	3 Aug 2011	14 Aug 2012	13 Aug 2013	4 Aug 2014
Midseason drainage	16 Aug 2009~23 Aug 2009	4 Sep 2010~8 Sep 2010	17 Aug 2011~23 Aug 2011	22 Aug 2012~1 Sep 2012	23 Aug 2013~4 Sep 2013	-
Second flooding	24 Aug 2009~6 Sep 2009	8 Sep 2010~29 Sep 2010	24 Aug 2011~4 Sep 2011	2 Sep 2012~1 Oct 2012	5 Sep 2013~19 Sep 2013	1 Sep 2014~22 Sep 2014
Panicle initiation fertilizers	30 Aug 2009	20 Sep 2010	23 Aug 2011	4 Sep 2012	4 Sep 2013	4 Sep 2014
Dry/wet alternation	7 Sep 2009~9 Oct 2009	30 Sep 2010~29 Oct 2010	5 Sep 2011~7 Oct 2011	3 Oct 2012~25 Oct 2012	20 Sep 2013~17 Oct 2013	23 Sep 2014~15 Oct 2014
Final drainage	10 Oct 2009	30 Oct 2010	8 Oct 2011	26 Oct 2012	18 Oct 2013	16 Oct 2014
Rice harvest	30 Oct 2009	1 Dec 2010	2 Nov 2011	4 Dec 2012	10 Nov 2013	6 Nov 2014

Table 2 The plant production and cultivation parameter files used to calibrate DAYCENT model for simulating CH_4 emission and grain yield.

Name of the file	Parameter	Description	Unit	Value
Crop.100	PRDX	Coefficient for calculating potential aboveground monthly production as a function of solar radiation outside the atmosphere	Scaling factor, (g C production) m^{-2} $month^{-1}$ $Langley^{-1}$	3.00
	PPDF (1)	Optimum temperature for production for parameterization of a Poisson Density Function curve to simulate temperature effect on growth	°C	25
	PPDF (2)	Maximum temperature for production for parameterization of a Poisson Density Function curve to simulate temperature effect on growth	°C	45
Sitepar.100	CO_2_to_CH_4	Fraction of CO_2 from soil respiration used to produce CH_4		0.15

Table 3 The crop parameters used to calibrate DNDC model for simulating CH_4 emission and grain yield.

Cropping season/parameter	**Grain**	**Leaf**	**Stem**	**Root**
Early rice (Zhongzao 33)				
Maximum biomass production (kg C ha^{-1} y^{-1})	8500	4829	4636	1352
Biomass fraction	0.44	0.25	0.24	0.07
Biomass C/N ratio	51	85	85	30
Thermal degree days	2000			
Water demand (g water/g DM)	508			
Optimum temperature (°C)	25			
Late rice (Nongxiang 98)				
Maximum biomass production (kg C ha^{-1} y^{-1})	8500	4829	4636	1352
Biomass fraction	0.44	0.25	0.24	0.07
Biomass C/N ratio	50	85	85	30
Thermal degree days	2850			
Water demand (g water/g DM)	508			
Optimum temperature (°C)	25			

Table 4. Comparison between the DAYCENT- and DNDC-simulated and measured average annual CH_4 (kg C ha^{-1} yr^{-1}) fluxes, early- and late-rice yield (t ha^{-1}), yield-scaled GHG emission (kg CO_2-eq ha^{-1} yr^{-1}) by the treatment of stubble incorporation (S), winter tillage with stubble incorporation (WS) and winter tillage (W). RD means relative deviation between simulated and measured emission/yield.

Treatments	Measured	DAYCENT	RD (%)	DNDC	RD (%)
Annual CH_4 flux (kg C ha^{-1} yr^{-1})					
S	175±26A[a]	173±15A	1	173±15A	1
WS	152±29AB	148±19AB	3	153±20A	-1
W	111±26B	138±18B	-24	117±22B	-5
Early rice yield (t ha^{-1})					
S	6.3±0.2A	6.4±0.4A	-1	6.1±0.3A	2
WS	6.6±0.3A	6.4±0.4A	3	6.7±0.6A	-2
W	6.5±0.2A	6.4±0.4A	2	7.0±0.8A	-8
Late rice yields (t ha^{-1})					
S	6.4±0.8A	6.3±0.8A	1	6.6±0.7A	-3
WS	6.5±0.9A	6.3±0.8A	4	6.8±0.7A	-4
W	6.3±0.9A	6.3±0.8A	0	6.7±0.7A	-6
Yield-scaled GHG_{CH4} (kg CO_2-eq ha^{-1} yr^{-1})					
S	0.52±0.03A	0.52±0.03A	0	0.51±0.03A	2
WS	0.43±0.03AB	0.44±0.03AB	-2	0.43±0.03AB	0
W	0.32±0.03B	0.41±0.03B	-28	0.32±0.03B	0

[a] Values followed by the same letter are not significantly different within the treatments at $p < 0.05$ based on Turkey tests.

Table 5. Statistical describing the performance of the DAYCENT and DNDC models for the simulations of daily CH_4 fluxes under different treatments in the double rice paddy from November 2008 to November 2014. The n is the number of measured CH_4 fluxes from November 2008 to November 2014.

Treatment	**Model**	**Measured (kg C ha^{-1})**	**RMSE (kg C ha^{-1})**	**rRMSE (%)**	**EF**	**r**	**M (kg C ha^{-1})**
S (n=398)	DAYCENT	0.67	0.85	127	0.28	0.60***	0.04^{ns}
	DNDC		0.85	128	0.27	0.61***	0.03^{ns}
WS (n=398)	DAYCENT	0.58	0.75	129	0.22	0.58***	0.04^{ns}
	DNDC		0.72	124	0.28	0.63***	0.02^{ns}
W (n=335)	DAYCENT	0.42	0.63	150	−0.07	0.59***	−0.08*
	DNDC		0.52	140	0.08	0.60***	−0.02^{ns}

[a] S, stubble incorporation without winter tillage; WS, winter tillage with stubble incorporation; W, winter tillage without stubble incorporation.

* Significant correlation (r) between modelled and measured values at $p < 0.05$, or significance mean error (M) at p=0.025.

*** Significant correlation (r) between modelled and measured values at $p < 0.001$.

^{ns} Non-significant between modelled and measured values at $p < 0.05$, or no significance mean error (M) at p=0.025.

Figure legends

Fig. 1. Sensitivity of CH_4 fluxes and yield to changes in the input parameters. SOC: soil organic carbon content (from 0.5 to 1.5 times the baseline). pH: soil pH (from "baseline − 1" to "baseline + 1"). N fer: application of N fertilizer (from 0.5 to 1.5 times the baseline). T: air temperature (from "baseline − 2" to "baseline + 2"). The SOC, pH, N fertilizer and daily average air temperature were 0.016 g kg^{-1}, 4.6, 360 kg N ha^{-1} and 18.16 ^{o}C.

Fig. 2. Comparison between the DAYCENT- and DNDC-simulated and measured daily CH_4 flux (Kg C ha^{-1} d^{-1}) from November 2008 to November 2014 for the treatments of stubble incorporation (S), winter tillage with stubble incorporation (WS) and winter tillage (W).

Fig. 3. Measured annual CH_4 emission (kg C ha^{-1} yr^{-1}) and yield (t ha^{-1} yr^{-1}) over the six annual rotation cycles from November 2008 to November 2014 for the treatments of stubble incorporation (S), winter tillage with stubble incorporation (WS) and winter tillage (W). Values are the means with standards deviations shown by vertical bars (n=3); uppercase letters indicate significant differences within years at $p < 0.05$.

Fig. 4. Comparison between DAYCENT- and DNDC-simulated and measured seasonal CH_4 (kg C ha^{-1}) for three treatments of stubble incorporation (S), winter tillage with stubble incorporation (WS) and winter tillage (W) from November 2008 to November 2014.

Fig. 5. Relationship between the DAYCENT- and DNDC-simulated and measured yields of early and late-paddy rice for the treatments of stubble incorporation (S), winter tillage with stubble incorporation (WS) and winter tillage (W).

Supporting Information for

Modelling methane emissions and grain yields for a double-rice system in Southern China with DAYCENT and DNDC

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Summary:

Number of Figures: 1

Number of Tables: 1

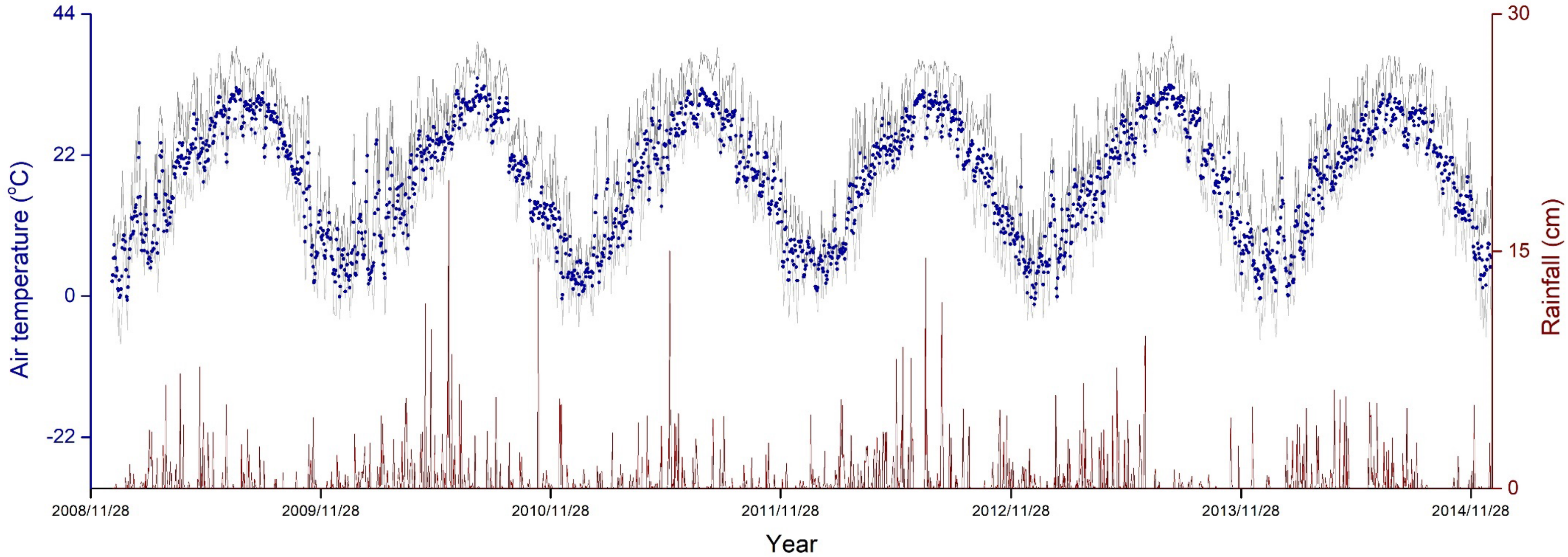

Fig. S1 Measured daily air temperature (°C) and rainfall (cm) during the experimental period (from November 2008 to November 2014) in the Yingtan of China.

Table S1 Monthly mean air temperature and rainfall from 2008 and 2014 at the field site.

Year/Month	Rainfall (cm)								Mean air temperature (ºC)							
	2008	2009	2010	2011	2012	2013	2014	Mean	2008	2009	2010	2011	2012	2013	2014	Mean
January	10	3.8	11.3	5.6	13.0	3.2	1.9	6.5	3.9	4.6	6.6	2.9	5.3	5.1	6.7	5.2
February	7.0	6.8	15.3	5.0	9.7	16.7	16.6	11.7	5.3	11.5	10.1	8.4	6.3	9.1	7.3	8.8
March	17.4	29.8	22.8	8.8	29.9	27.5	28.3	24.5	13.6	12.6	12.5	11.2	11.7	13.9	13.4	12.5
April	25.8	19.0	34.5	15.2	25.2	20.4	16.1	21.7	19.0	19.1	15.5	19.1	19.3	16.9	19.3	18.2
May	14.2	18.5	41.5	11.9	36.2	25.2	21.5	25.8	23.8	23.0	22.7	22.5	23.3	23.4	22.3	22.9
June	26.1	10.3	58.3	49.4	38.3	39.8	22.8	36.5	25.8	27.1	24.5	26.1	26.0	26.4	25.8	26.0
July	18.9	12.1	22.2	11.8	25.1	2.8	22.6	16.1	29.7	29.2	29.6	29.9	29.8	30.1	28.8	29.6
August	5.9	14.0	7.4	19.2	36.2	3.3	15.4	15.9	29.1	29.0	29.9	28.8	28.5	30.6	27.5	29.1
September	5.2	2.3	14.0	2.0	14.4	3.4	4.1	6.7	26.7	26.9	26.6	25.2	23.3	25.2	26.5	25.6
October	6.1	1.3	7.6	6.5	3.5	1.8	0.3	3.5	20.6	20.8	18.4	19.3	19.6	19.3	20.6	19.6
November	13.0	13.2	18.4	7.1	25.5	11.5	6.7	13.7	12.5	10.8	13.4	16.5	11.9	13.2	14.4	13.4
December	2.1	6.7	20.3	4.2	13.2	7.6	9.5	10.2	7.2	6.9	7.9	6.7	6.5	5.9	6.0	6.6

Table

Table 1 Schedule of field management practices in the experimental plots over the six years from November 20108 to November 2014.

Season	Field Management	2008-2009	2009-2010	2010-2011	2011-2012	2012-2013	2013-2014
Winter fallow	Winter tillage	8 Nov 2008	13 Nov 2009	2 Dec 2010	3 Nov 2011	5 Dec 2012	11 Nov 2013
Early-rice	Spring tillage	12 Apr 2009	17 Apr 2010	19 Apr 2011	23 Apr 2012	20 Apr 2013	10 Apr 2014
	First flooding	13 Apr 2009	17 Apr 2010	21 Apr 2011	23 Apr 2012	22 Apr 2013	10 Apr 2014
	Basal fertilizers	17 Apr 2009	26 Apr 2010	22 Apr 2011	27 Apr 2012	24 Apr 2013	13 Apr 2014
	Rice translates	17 Apr 2009	27 Apr 2010	23 Apr 2011	27 Apr 2012	24 Apr 2013	13 Apr 2014
	Tillering fertilizers	26 Apr 2009	11 May 2010	14 May 2011	15 May 2012	17 May 2013	29 Apr 2014
	Midseason drainage	8 May 2009~15 May 2009	23 May 2010~27 May 2010	23 May 2011~31 May 2011	25 May 2012~5 Jun 2012	28 May 2013~3 Jun 2013	22 May 2014~29 May 2014
	Second flooding	16 May 2009~2 Jun 2009	28 May 2010~2 Jun 2010	1 Jun 2011~24 Jun 2011	6 Jun 2012~18 Jun 2012	-	30 May 2014~16 Jun 2014
	Panicle initiation fertilizers	26 May 2009	12 Jun 2010	16 Jun 2011	12 Jun 2012	14 Jun 2013	10 Jun 2014
	Dry/wet alternation	3 Jun 2009~3 Jul 2009	22 Jun 2010~15 Jul 2010	25 Jun 2011~3 Jul 2011	19 Jun 2012~23 Jun 2012	-	17 Jun 2014~29 Jun 2014
	Final drainage	4 Jul 2009	16 Jul 2010	4 Jul 2011	24 Jun 2012	4 Jul 2013	30 Jun 2014
	Rice harvest	9 Jul 2009	22 Jul 2010	11 Jul 2011	13 Jul 2012	18 Jul 2013	16 Jul 2014
Late-rice	Tillage	10 Jul 2009	31 Jul 2010	11 Jul 2011	14 Jul 2012	22 Jul 2013	19 Jul 2014
	First flooding	12 Jul 2009	31 Jul 2010	12 Jul 2011	15 Jul 2012	24 Jul 2013	20 Jul 2014
	Basal fertilizers	14 Jul 2009	5 Aug 2010	16 Jul 2011	27 Jul 2012	24 Jul 2013	22 Jul 2014

Rice translates	15 Jul 2009	5 Aug 2010	16 Jul 2011	27 Jul 2012	24 Jul 2013	22 Jul 2014
Tillering fertilizers	29 Jul 2009	23 Aug 2010	3 Aug 2011	14 Aug 2012	13 Aug 2013	4 Aug 2014
Midseason drainage	16 Aug 2009~23 Aug 2009	4 Sep 2010~8 Sep 2010	17 Aug 2011~23 Aug 2011	22 Aug 2012~1 Sep 2012	23 Aug 2013~4 Sep 2013	-
Second flooding	24 Aug 2009~6 Sep 2009	8 Sep 2010~29 Sep 2010	24 Aug 2011~4 Sep 2011	2 Sep 2012~1 Oct 2012	5 Sep 2013~19 Sep 2013	1 Sep 2014~22 Sep 2014
Panicle initiation fertilizers	30 Aug 2009	20 Sep 2010	23 Aug 2011	4 Sep 2012	4 Sep 2013	4 Sep 2014
Dry/wet alternation	7 Sep 2009~9 Oct 2009	30 Sep 2010~29 Oct 2010	5 Sep 2011~7 Oct 2011	3 Oct 2012~25 Oct 2012	20 Sep 2013~17 Oct 2013	23 Sep 2014~15 Oct 2014
Final drainage	10 Oct 2009	30 Oct 2010	8 Oct 2011	26 Oct 2012	18 Oct 2013	16 Oct 2014
Rice harvest	30 Oct 2009	1 Dec 2010	2 Nov 2011	4 Dec 2012	10 Nov 2013	6 Nov 2014

Table 2 The plant production and cultivation parameter files used to calibrate DAYCENT model for simulating CH_4 emission and grain yield.

Name of the file	Parameter	Description	Unit	Value
Crop.100	PRDX	Coefficient for calculating potential aboveground monthly production as a function of solar radiation outside the atmosphere	Scaling factor, (g C production) m^{-2} $month^{-1}$ $Langley^{-1}$	3.00
	PPDF (1)	Optimum temperature for production for parameterization of a Poisson Density Function curve to simulate temperature effect on growth	°C	25
	PPDF (2)	Maximum temperature for production for parameterization of a Poisson Density Function curve to simulate temperature effect on growth	°C	45
Sitepar.100	CO_2_to_CH_4	Fraction of CO_2 from soil respiration used to produce CH_4		0.15

Table 3 The crop parameters used to calibrate DNDC model for simulating CH_4 emission and grain yield.

Cropping season/parameter	Grain	Leaf	Stem	Root
Early rice (Zhongzao 33)				
Maximum biomass production (kg C ha^{-1} y^{-1})	8500	4829	4636	1352
Biomass fraction	0.44	0.25	0.24	0.07
Biomass C/N ratio	51	85	85	30
Thermal degree days	2000			
Water demand (g water/g DM)	508			
Optimum temperature (°C)	25			
Late rice (Nongxiang 98)				
Maximum biomass production (kg C ha^{-1} y^{-1})	8500	4829	4636	1352
Biomass fraction	0.44	0.25	0.24	0.07
Biomass C/N ratio	50	85	85	30
Thermal degree days	2850			
Water demand (g water/g DM)	508			
Optimum temperature (°C)	25			

Table 4. Comparison between the DAYCENT- and DNDC-simulated and measured average annual CH_4 (kg C ha^{-1} yr^{-1}) fluxes, early- and late-rice yield (t ha^{-1}), yield-scaled GHG emission (kg CO_2-eq ha^{-1} yr^{-1}) by the treatment of stubble incorporation (S), winter tillage with stubble incorporation (WS) and winter tillage (W). RD means relative deviation between simulated and measured emission/yield.

Treatments	Measured	DAYCENT	RD (%)	DNDC	RD (%)
Annual CH_4 flux (kg C ha^{-1} yr^{-1})					
S	175±26A[a]	173±15A	1	173±15A	1
WS	152±29AB	148±19AB	3	153±20A	-1
W	111±26B	138±18B	-24	117±22B	-5
Early rice yield (t ha^{-1})					
S	6.3±0.2A	6.4±0.4A	-1	6.1±0.3A	2
WS	6.6±0.3A	6.4±0.4A	3	6.7±0.6A	-2
W	6.5±0.2A	6.4±0.4A	2	7.0±0.8A	-8
Late rice yields (t ha^{-1})					
S	6.4±0.8A	6.3±0.8A	1	6.6±0.7A	-3
WS	6.5±0.9A	6.3±0.8A	4	6.8±0.7A	-4
W	6.3±0.9A	6.3±0.8A	0	6.7±0.7A	-6
Yield-scaled GHG_{CH4} (kg CO_2-eq ha^{-1} yr^{-1})					
S	0.52±0.03A	0.52±0.03A	0	0.51±0.03A	2
WS	0.43±0.03AB	0.44±0.03AB	-2	0.43±0.03AB	0
W	0.32±0.03B	0.41±0.03B	-28	0.32±0.03B	0

[a] Values followed by the same letter are not significantly different within the treatments at $p < 0.05$ based on Turkey tests.

Table 5. Statistical describing the performance of the DAYCENT and DNDC models for the simulations of daily CH_4 fluxes under different treatments in the double rice paddy from November 2008 to November 2014. The n is the number of measured CH_4 fluxes from November 2008 to November 2014.

Treatment	**Model**	**Measured (kg C ha^{-1})**	**RMSE (kg C ha^{-1})**	**rRMSE (%)**	**EF**	**r**	**M (kg C ha^{-1})**
S (n=398)	DAYCENT	0.67	0.85	127	0.28	0.60***	0.04^{ns}
	DNDC		0.85	128	0.27	0.61***	0.03^{ns}
WS (n=398)	DAYCENT	0.58	0.75	129	0.22	0.58***	0.04^{ns}
	DNDC		0.72	124	0.28	0.63***	0.02^{ns}
W (n=335)	DAYCENT	0.42	0.63	150	−0.07	0.59***	−0.08*
	DNDC		0.52	140	0.08	0.60***	−0.02^{ns}

[a] S, stubble incorporation without winter tillage; WS, winter tillage with stubble incorporation; W, winter tillage without stubble incorporation.

* Significant correlation (r) between modelled and measured values at $p < 0.05$, or significance mean error (M) at p=0.025.

*** Significant correlation (r) between modelled and measured values at $p < 0.001$.

^{ns} Non-significant between modelled and measured values at $p < 0.05$, or no significance mean error (M) at p=0.025.

Figure legends

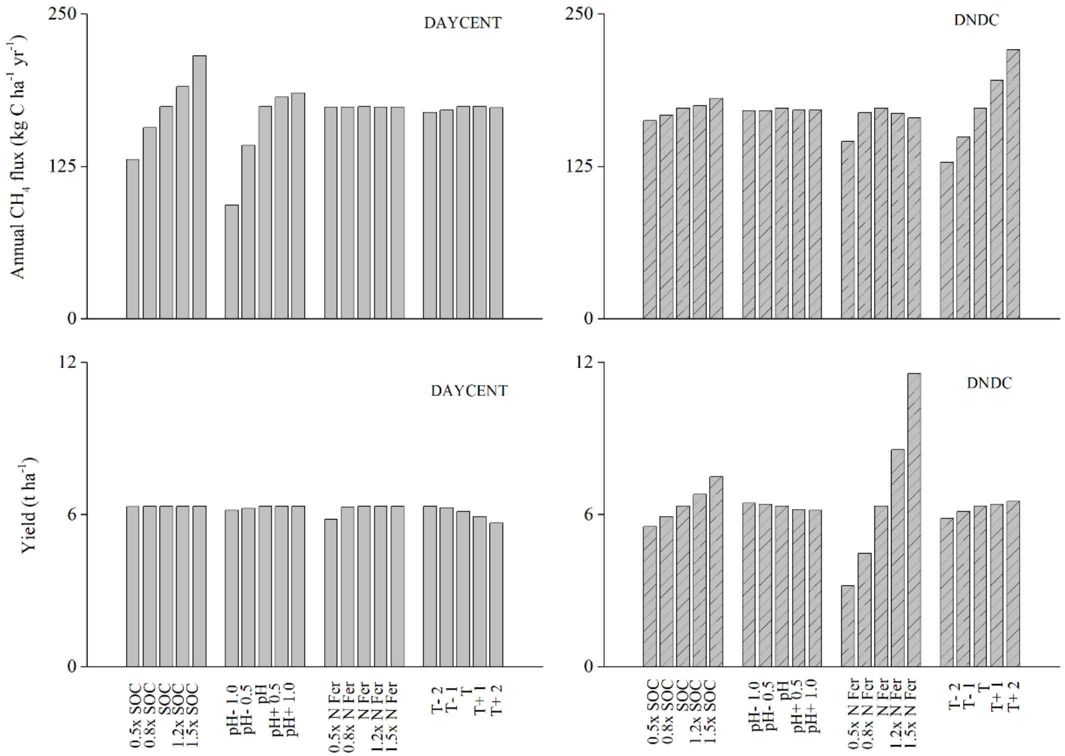

Fig. 1. Sensitivity of CH_4 fluxes and yield to changes in the input parameters. SOC: soil organic carbon content (from 0.5 to 1.5 times the baseline). pH: soil pH (from "baseline − 1" to "baseline + 1"). N fer: application of N fertilizer (from 0.5 to 1.5 times the baseline). T: air temperature (from "baseline − 2" to "baseline + 2"). The SOC, pH, N fertilizer and daily average air temperature were 0.016 g kg^{-1}, 4.6, 360 kg N ha^{-1} and 18.16 ºC.

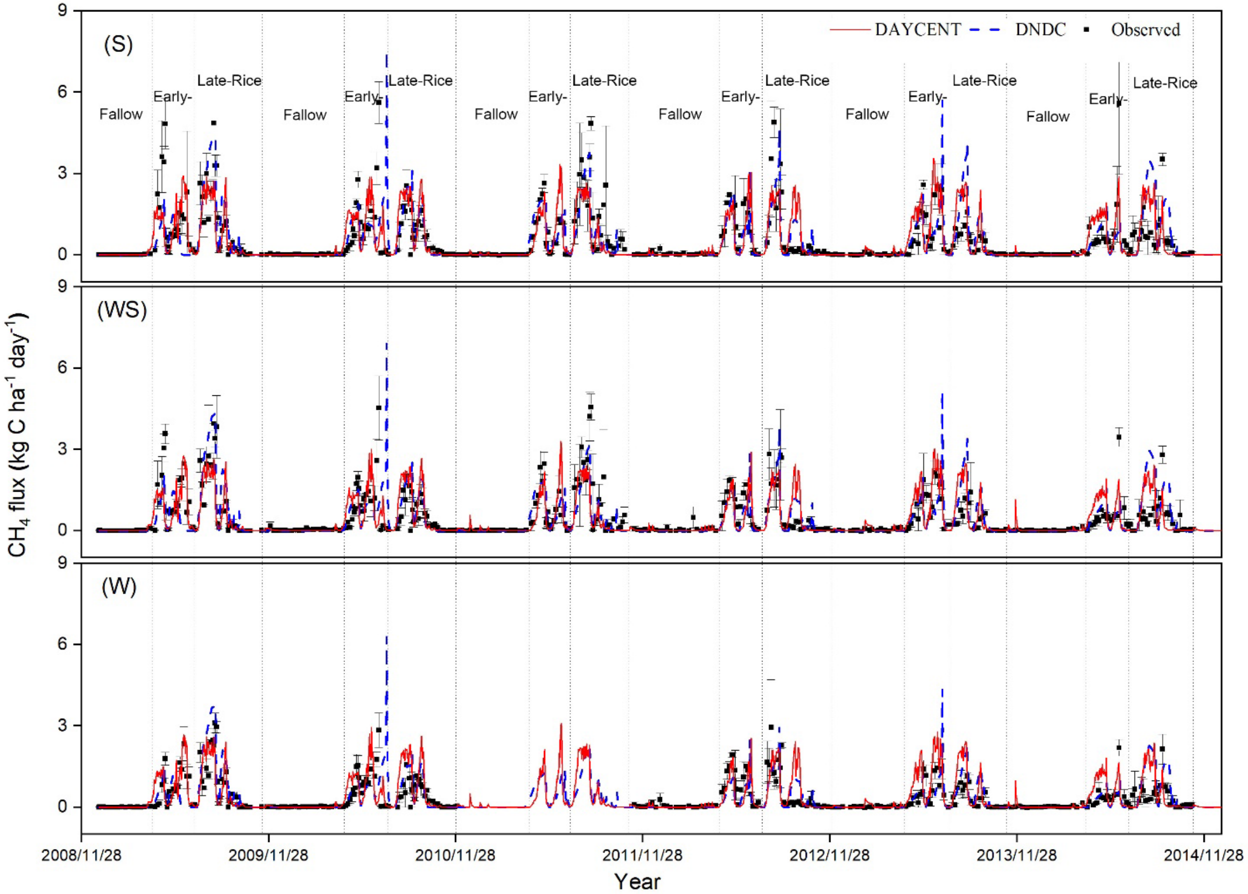

Fig. 2. Comparison between the DAYCENT- and DNDC-simulated and measured daily CH_4 flux (Kg C ha^{-1} d^{-1}) from November 2008 to November 2014 for the treatments of stubble incorporation (S), winter tillage with stubble incorporation (WS) and winter tillage (W).

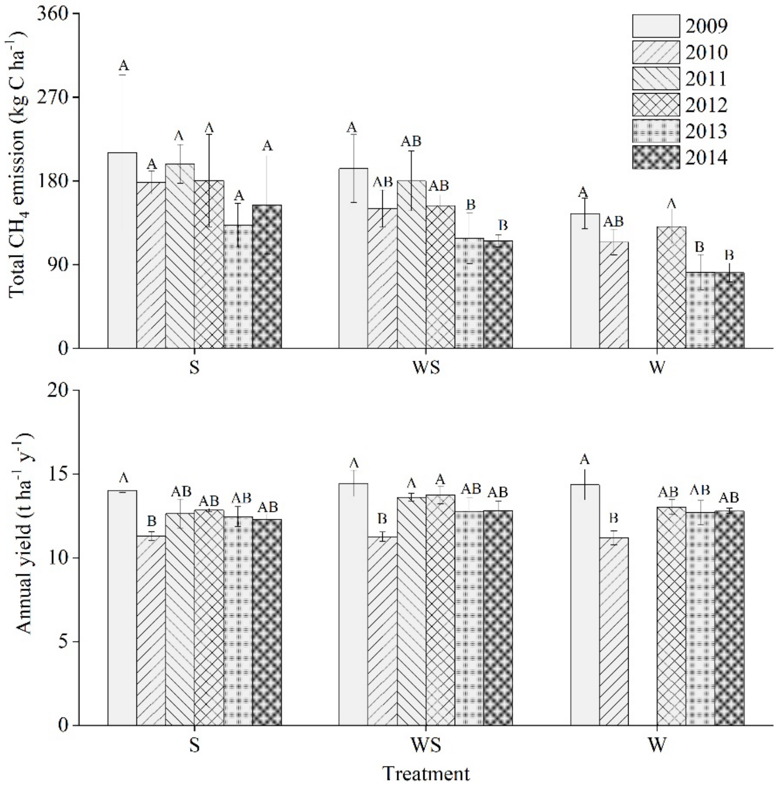

Fig. 3. Measured annual CH_4 emission (kg C ha-1 yr-1) and yield (t ha-1 yr-1) over the six annual rotation cycles from November 2008 to November 2014 for the treatments of stubble incorporation (S), winter tillage with stubble incorporation (WS) and winter tillage (W). Values are the means with standards deviations shown by vertical bars (n=3); uppercase letters indicate significant differences within years at $p < 0.05$.

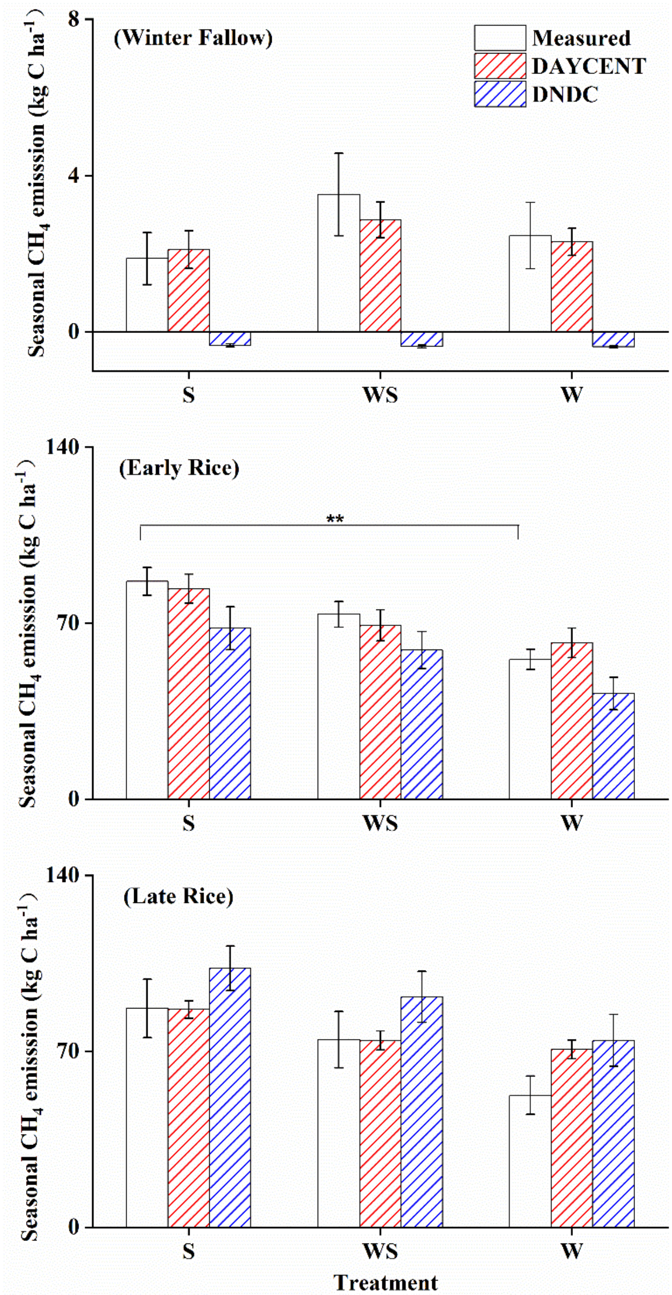

Fig. 4. Comparison between DAYCENT- and DNDC-simulated and measured seasonal CH_4 (kg C ha^{-1}) for three treatments of stubble incorporation (S), winter tillage with stubble incorporation (WS) and winter tillage (W) from November 2008 to November 2014.

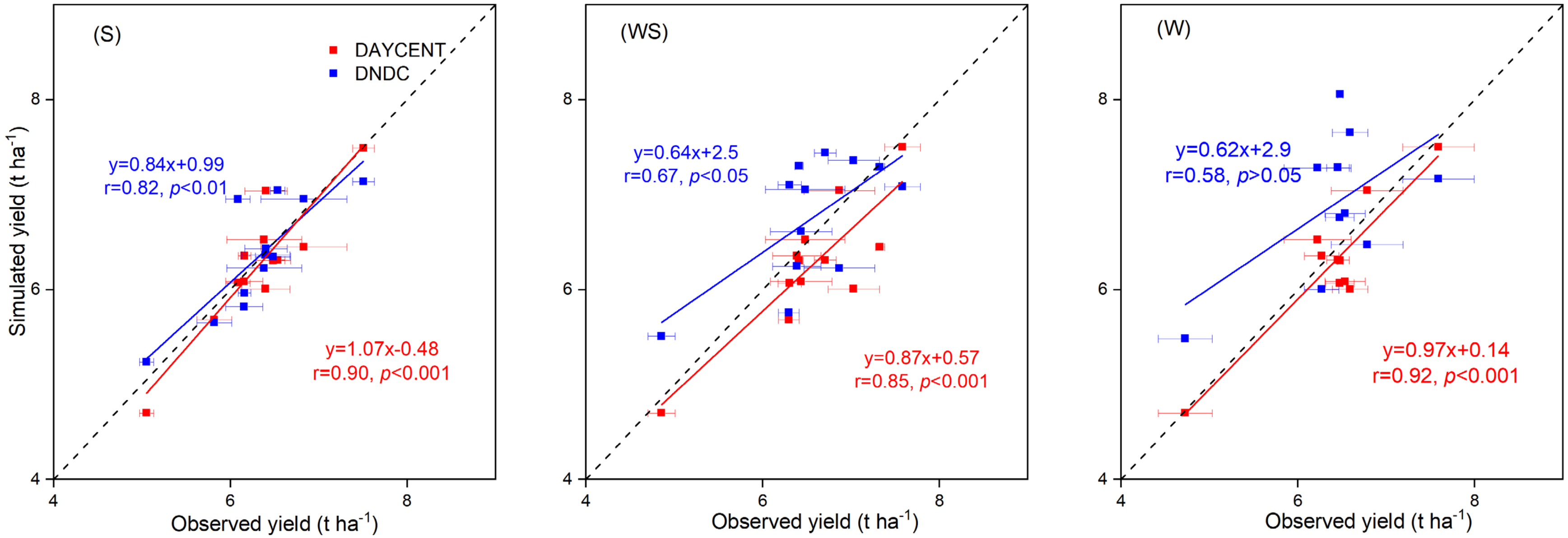

Fig. 5. Relationship between the DAYCENT- and DNDC-simulated and measured yields of early and late-paddy rice for the treatments of stubble incorporation (S), winter tillage with stubble incorporation (WS) and winter tillage (W).