**Prediction of future methane emission from irrigated rice paddies in central
Thailand under different water management practices**

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ABSTRACT

There is concern about positive feedbacks between climate change and methane (CH₄) emission from rice paddies. However, appropriate water management may mitigate the problem. We tested this hypothesis at six field sites in central Thailand, where the irrigated area is rapidly increasing. We used DNDC-Rice, a process-based biogeochemistry model adjusted based on rice growth data at each site to simulate CH₄ emission from a rice-rice double cropping system from 2001 to 2060. Future climate change scenarios consisting of four representative concentration pathways (RCPs) and seven global climate models were generated by statistical downscaling. We then simulated CH₄ emission in three water management practices: continuous flooding (CF), single aeration (SA), and multiple aeration (MA). The adjusted model reproduced the observed rice yield and CH₄ emission well at each site. The simulated CH₄ emissions in CF from 2051 to 2060 were 5.3 to 7.8%, 9.6 to 16.0%, 7.3 to 18.0%, and 13.6 to 19.0% higher than those from 2001 to 2010 in RCPs 2.6, 4.5, 6.0, and 8.5, respectively, at the six sites. Regionally, SA and MA mitigated CH₄ emission by 21.9 to 22.9% and 53.5 to 55.2%, respectively, relative to CF among the four RCPs. **These mitigation potentials by SA and MA were comparable to those from 2001 to 2010.** Our results indicate that **climate change in the next several decades will not attenuate the quantitative effect of** water management **practices on** mitigating CH₄ emission from irrigated rice paddies in central Thailand.

Keywords

DNDC-Rice, Global warming, Intermittent irrigation, Midseason drainage, Regional climate downscaling

1. Introduction

Methane (CH₄) is the second-most-important greenhouse gas after carbon dioxide (CO₂). Although CH₄ has a relatively short lifetime in the atmosphere, it is estimated to have 34 times the global warming potential of CO₂ for a time horizon of 100 years when including climate-carbon feedbacks (Myhre et al., 2013). Thus, immediate mitigation actions can reduce the risk of crossing the critical 2°C threshold for the global air temperature rise more than a reduction of CO₂ emission alone (Shindell et al., 2012).

Rice is a staple food for half of the world's population, and 90% of the world's rice is produced in Asia (GRiSP, 2013). However, rice cultivation is one of the major anthropogenic sources of atmospheric CH₄ (Ciais et al., 2013). GRiSP (2013) projected that global rice demand would rise from 439 Tg (milled rice) in 2010 to 555 Tg in 2035 due to increases in the human population. This suggests that rice cultivation will remain important as a major anthropogenic CH₄ source. Furthermore, future climate change caused by the increasing atmospheric CO₂ concentration ([CO₂]) and rising air temperatures may increase the emission of CH₄ from rice paddies (van Groenigen et al., 2011, 2013).

Irrigated rice paddies exhibit the highest productivity among rice ecosystems; however, the potential CH₄ emission is also highest because of the longer flooded period and greater return of crop residues to the soil. Thailand is the world's largest rice exporter and the sixth largest rice producer (FAOSTAT, 2016). Recently, the proportion of the total rice area has been rapidly increasing for irrigated rice, from 23.8% in 1995 to 58.8% in 2007 (AQUASTAT, 2016; FAOSTAT, 2016). Especially in central Thailand, a large proportion of the rice area already has access to irrigation facilities, which enables farmers to grow two rice crops per year, with a second crop during the dry season (GRiSP, 2013). Therefore, the spread of a rice-rice double cropping system under irrigated conditions will increase the potential CH₄

1 emission from rice paddies in Thailand.

2 The primary purpose of water management in irrigated rice paddies depends on the
3 environmental situation. The practices adopted in East Asia are often called “midseason
4 drainage” and “intermittent irrigation.” These practices aim to improve rice growth by
5 controlling surplus tillering and supplying rice roots with molecular oxygen (O_2) to prevent
6 sulfide toxicity (Kanno et al., 1997). Another practice, originally developed by the
7 International Rice Research Institute, called “alternate wetting and drying (AWD)” aims to
8 reduce the volume of irrigation water consumed in rice cultivation, especially during the dry
9 season (IRRI, 2015). Water management is one of the most promising options to mitigate CH_4
10 emission from irrigated rice paddies, since it leads to the development of aerobic soil
11 conditions that reduce CH_4 production. The 2006 IPCC Guidelines for National Greenhouse
12 Gas Inventories adopted values of 0.60 (error range: 0.46 to 0.80) and 0.52 (0.41 to 0.66) as
13 the scaling factor for water regime under single aeration (SA) and multiple aeration (MA),
14 respectively, compared to 1 (0.79 to 1.26) under continuous flooding (CF) in the
15 disaggregated case of irrigated rice paddies (IPCC, 2006).

16 We hypothesized that appropriate water management practices could mitigate the CH_4
17 emission from irrigated rice paddies **even** under future climate change. Especially in Thailand,
18 rice cultivation is the most important agricultural greenhouse gas source, and accounted for
19 57% of the total agricultural emission in 2000 (ONREPP, 2010). Accordingly, mitigation of
20 CH_4 emission from rice paddies would support national efforts to reduce greenhouse gas
21 emissions under the United Nations Framework Convention on Climate Change. However, at
22 the same time, future climate change will affect the dynamics of soil organic carbon (SOC),
23 which is an important factor in controlling both plant productivity (Lal, 2004) and paddy CH_4
24 emission (Yan et al., 2005).

25 The objective of the present study was to test the abovementioned hypothesis, using rice

production in Thailand as a case study. We used a process-based biogeochemistry model, DNDC-Rice (Fumoto et al., 2008) to predict future CH₄ emission from irrigated rice paddies in central Thailand under different water management practices. First, we adjusted the model using crop data from six experimental sites. Then, we simulated CH₄ emission from each site during the period from 2001 to 2060 under various climate scenarios that were generated by means of regional downscaling from seven global climate models (GCMs) under four representative concentration pathways (RCPs). Finally, we compared the effect of water management practices on mitigating CH₄ emission between present and future climate conditions.

2. Methods

2.1. Model description

DNDC-Rice is a member of the family of DNDC (DeNitrification DeComposition) models, originally developed by Li et al. (1992), and improved DNDC's capacity to model paddy biogeochemistry by refining the description of CH₄ production (Gilhespy et al., 2014). Fumoto et al. (2008, 2010) provided detailed features of DNDC-Rice, and Table S1 summarizes the history of DNDC-Rice modeling. Version 1.0 of DNDC-Rice was validated for nine irrigated rice paddies across Thailand (Smakgahn et al., 2009), and version 2.0 was validated for an irrigated rice paddy in Japan under a free-air CO₂ enrichment (FACE) treatment (Fumoto et al., 2013). However, version 2.0 of DNDC-Rice, which employed the MACROS crop model (Penning de Vries et al., 1989), did not adequately reproduce the effects of elevated [CO₂] on rice growth and CH₄ emission.

DNDC-Rice consists of three major submodels, which simulate crop growth, soil climate,

1 and soil biogeochemistry. In the rest of this section, we summarize the model's responses to
2 climate and water management.

3 To calculate the photosynthetic rate of rice per unit leaf area under the effects of changing
4 air temperature and $[\text{CO}_2]$, the version of DNDC-Rice used in the present study (3.0)
5 employed the model of Farquhar and von Caemmerer (1982) as part of the crop growth
6 submodel, in a way similar to that of Yoshida et al. (2015). In an intercomparison of 13 rice
7 crop models against multi-year experimental data at four sites in Asia (Li et al., 2015), version
8 3.0 of DNDC-Rice exhibited the second- and third-best coefficient of determination (R^2) with
9 measured rice grain yield and aboveground biomass, respectively, with calibration only for
10 rice phenology. To implement the Farquhar–von Caemmerer model in DNDC-Rice, the
11 maximum carboxylation rate ($V_{c_{\max}}$) and the light-saturated potential rate of electron transport
12 ($J_{\max}$) are described as functions of the leaf nitrogen concentration (N_{LA}), based on
13 observations from a FACE experiment in Japan (Hasegawa et al., 2015). Simulation of the
14 effects of water stress on rice growth can be turned on or off in the model; it was turned off in
15 the present study because the observed rice aboveground biomass did not differ significantly
16 among four water management practices, similar to those in the present study, at the Samut
17 Sakhon site in central Thailand (Towprayoon et al., 2005).

18 The soil climate submodel divides soil profile to a depth of 50 cm into layers ca. 1.5 cm
19 thick and simulates one-dimensional transport of water, heat, and O_2 between the layers and
20 between the soil and the atmosphere based on the soil's properties, daily weather conditions,
21 and agricultural practices. The O_2 transport is simulated by a diffusion model that relates the
22 diffusion coefficient to the gas-phase volume.

23 The soil biogeochemistry submodel simulates various biogeochemical processes as a
24 function of soil properties and the environmental conditions. Under anaerobic soil conditions,
25 the submodel calculates the production of hydrogen (H_2) and dissolved organic carbon (DOC),

1 which are used as electron donors for the subsequent reduction of oxidants [Mn(IV), Fe(III),
2 SO_4^{2-}] and CH_4 production. The rates of oxidant reduction and CH_4 production are calculated
3 using the Michaelis–Menten equation. CH_4 production is therefore inhibited by competition
4 among the abovementioned oxidants for H_2 and DOC. When a paddy soil is drained, CH_4 and
5 reduced oxidants [Mn(II), Fe(II), and H_2S] are oxidized by O_2 that diffuses into the soil from
6 the atmosphere. The oxidized Mn, Fe, and S again act as electron acceptors under subsequent
7 anaerobic conditions.

8 9 *2.2. Site locations and data collection*

10
11 We selected six experimental sites in central Thailand that provided sufficient data to
12 parameterize the model's input parameters, based on the descriptions in four peer-reviewed
13 papers. From north to south, the sites were Chai Nat, Suphan Buri, Khlong Luang, Pathum
14 Thani, Samut Sakhon, and Ratchaburi (Fig. 1).

15 The data on the crop calendar, field management practices, and soil properties at each site
16 (Table 1) were compiled from the published papers, supplemented by data from Thai literature
17 when necessary. The year and treatment in the field experiments differed among the sites. The
18 effects of water management practices on rice grain yield and CH_4 emission were only studied
19 at the Samut Sakhon site (Jiaphasuanan and Towprayoon, 2014; Towprayoon et al., 2005).

20 Modeling using DNDC-Rice requires daily maximum and minimum air temperatures, daily
21 precipitation, and daily solar radiation as essential weather input parameters. Except for daily
22 solar radiation, weather data were obtained from the Thailand Meteorological Agency station
23 nearest to each site (<10 km) for the experimental year and the previous years. Daily solar
24 radiation (S) was estimated from the recorded daily sunshine duration (N) using the following
25 equations:

$$S / S_o = a + b (N / N_o), \text{ if } (0 < N / N_o \leq 1) \quad (1)$$

$$S / S_o = c, \text{ if } (N / N_o = 0) \quad (2)$$

where N_o is the day length and S_o is the downward shortwave radiation at the top of atmosphere. a , b , and c are empirical coefficients which were derived by regression analysis of observed shortwave radiation and sunshine duration obtained from the observation stations in Thailand (Ishigooka et al., 2010).

2.3. Model modification and adjustment

We made a minor modification to the model's description of SOC dynamics. In DNDC-Rice, the SOC pool consists of the following three conceptual fractions, from labile to recalcitrant: litter, humads, and humus. A preliminary run of version 3.0 DNDC-Rice for a period of several decades indicated considerable loss of the humus fraction (data not shown). This had not been accounted for in previous studies that employed DNDC-Rice (see Table S1) because those studies focused on shorter terms. Although there are no long-term data available on SOC dynamics in Thai rice paddies, a long-term case study in the Philippines suggested that rice-rice double cropping with post-harvest incorporation of the crop residues resulted in stable or slightly increased SOC storage during the 15 years of the study (Pampolino et al., 2008). We therefore modified the decomposition rate of the humus fraction to be 0.7 times the default value, based on the assumption that SOC storage in the top 30 cm of the soil will be relatively stable if (1) biomass production under a rice-rice double cropping is normal and (2) the initial SOC storage is normal (see Fig. S1).

Modeling using DNDC-Rice requires the determination of daily developmental rate

constants during the vegetative and reproductive stages of rice (i.e., before and after heading, respectively). In accordance with the established practice, we adjusted the two rate constants by setting the simulated heading and maturation dates to the dates observed at each site (Table 1). The biologically reducible iron content (Table 1) is the most important parameter for calculation of the soil electron budget in the model. However, because this parameter was not observed at any of the study sites, we estimated it from a regression formula based on the free iron oxide content (Hayano et al., 2013; Smakgahn et al., 2009). The daily maximum iron reduction rate was set at 5% of the biologically reducible iron content, following the method in a previous study (Katayanagi et al., 2012).

Modeling with DNDC-Rice also requires a spin-up period to achieve a near-steady-state level of SOC storage before the main simulation. Following the established practice (Fumoto et al., 2008), the spin-up was performed for a period of 20 years with continuous weather observation data and the fixed crop calendar at each site (Table 1). Rice grain yield and CH₄ emission in the target year were simulated following the spin-up period.

The simulated rice grain yield and CH₄ emission were compared with the observed data at each site. The R^2 and the normalized root-mean-square error (NRMSE; Katayanagi et al., 2013) were used to evaluate the goodness of fit and to compare the model's performance with previous studies that employed DNDC-Rice for multi-site simulations.

2.4. Prediction of future CH₄ emission

2.4.1. Field management assumptions and scenarios

We assumed that the following three field management practices were shared among the six sites for the simulation of CH₄ emission from 2001 to 2060. First, each site adopted a rice-rice double cropping system with seedling transplanting, even if transplanting had not

1 been adopted in the field experiment. Rice was cultivated in the dry season (mainly January to
2 May) as well as the rainy season (July to December) in the long-term simulation (Table 1).
3 Local farmers will grow rice even in the dry season if the field is irrigated. Second, the crop
4 calendar and agricultural practices used the same values as those in the field experiment
5 (Table 1). Thai farmers will not drastically change the crop calendar in response to climate
6 change because local air temperature is high throughout the year. Third, all of the rice straw
7 was incorporated into the topsoil after harvesting, without any additional organic amendment.
8 Although the total amount of incorporated straw differed among the sites (see Fig. S1), this
9 organic management is both feasible and a reasonable way to maintain soil fertility and SOC
10 storage.

11 We developed the following three water-management scenarios: CF, SA, and MA. We
12 regarded CF as the baseline scenario, in which the field was irrigated just before transplanting
13 and then kept flooded until the final drainage 10 days before harvest. SA represents a regime
14 with the midseason drainage, in which the field was drained for 10 days at 1 month after
15 transplanting and then re-flooded until the final drainage. MA denotes the combination of
16 midseason drainage with intermittent irrigation, in which the field experienced cycles of 3
17 days of flooding followed by 4 days of drainage after the midseason drainage until the final
18 drainage.

20 2.4.2. *Climate change scenarios*

21 To simulate the effects of climate change, we generated scenarios consisting of four RCPs
22 and seven GCMs at four Thailand Meteorological Agency stations (Chai Nat, Suphan Buri,
23 Bang Na, and Ratchaburi; Fig. 1) for the period from 1981 to 2060. The dataset we generated
24 is available from an online database
25 (http://dias-dmg.tkl.iis.u-tokyo.ac.jp/dmm/doc/JP_NIAES_AgroMet_StationData_Thailand-D

IAS-en.html). The mean [CO₂] at the start of the simulation (2001 to 2010) was 380 ppmv and those at the end of the simulation (2051 to 2060) under RCPs 2.6, 4.5, 6.0, and 8.5 (which represent radiative forcing of +2.6, +4.5, +6.0, and +8.5 W m⁻², respectively) were 442, 499, 495, and 574 ppmv, respectively (Moss et al., 2010). Note that the mean [CO₂] under RCPs 4.5 and 6.0 at the end of the simulation are almost the same although the mean [CO₂] under RCP6.0 at the end of 21st century is higher than that under RCP4.5.

The scenarios were based on the daily outputs of the GCMs archived in the Coupled Model Intercomparison Project phase 5 multi-model ensemble dataset (Taylor et al., 2012). The seven GCMs we used were GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR, MIROC5, MIROC-ESM-CHEM, MRI-CGCM3, and NorESM1-M (<http://cmip-pcmdi.llnl.gov/cmip5/availability.html>). Although more GCMs are available, we selected these seven based on their ability to provide data for the climate variables that are essential to run DNDC-Rice. For all seven GCMs, we used a single climate representation (“run 1”) if multiple ensemble members were available for a GCM.

We corrected the biases in the daily GCM data using a downscaling method based on the cumulative distribution function (Iizumi et al., 2010, 2011, 2012). Site-based daily weather data from 1976 to 2005 were used as the baseline, but the exact number of years used varied among the sites due to differences in availability of the data. At the Suphan Buri site, no solar radiation data were available during that period, thus we used data from the GRASP meteorological forcing dataset for global crop modeling (Iizumi et al., 2014) as a reference, since it provides an estimate of solar radiation derived by correcting for biases in the reanalysis data using satellite-derived reference data. Iizumi et al. (2014) provided details of the method. The daily weather data at the Bang Na station were used for the Khlong Luang, Pathum Thani, and Samut Sakhon sites because these sites were distributed within the same grid cell of the GCMs, and we therefore expected no remarkable spatial variations in their

future climate change scenarios. The variations in topography and associated local climate conditions among these sites were also relatively small compared to the differences among the remaining sites. For these reasons, we justified the use of the same climate change scenarios across these four sites and believe that this did not influence our findings.

2.4.3. Long-term simulation and its analysis

Following the 20-year spin-up from 1981 to 2000, we performed a 60-year simulation from 2001 to 2060 for each site using the adjusted model and the generated continuous 80-year daily weather data. The agreement of the daily weather data between the observations and the scenarios from 1981 to 2005 was confirmed in spite of the different data availability as described above (data not shown). The total number of simulations was 504 (i.e., 4 RCPs $\times$ 7 GCMs $\times$ 6 sites $\times$ 3 practices). We did not address nitrous oxide (N₂O) emission in the present study because observed N₂O emission data were not available at most sites to evaluate the model's performance. In addition, even if this data had been available, the contribution of N₂O to the total global warming potential of CH₄ and N₂O was likely to be negligible based on observations at the Samut Sakhon site (Towprayoon et al., 2005).

We then analyzed the effect of water management on the simulated CH₄ emission, and compared the effect between the start and end of the simulation period for each site. A mean simulated CH₄ emission was considered to differ significantly from another mean if their 95% confidence intervals (CIs) among the seven GCMs or among the six sites did not overlap, and were significantly different from zero if the 95% CI did not overlap zero; this follows the method of Gurevitch and Hedges (1993).

We also analyzed the effect of climate change on the increase in CH₄ emission by comparing the mean CH₄ emission at the start and end of the simulation period. In addition, we performed a sensitivity analysis to separate the effect of climate change (i.e., [CO₂] + air

temperature) on CH₄ emission into [CO₂] and air temperature components for the CF practice at the Suphan Buri site under RCP4.5 as an example for a site with intermediate values of SOC dynamics and biomass production (see Fig. S1). The 60-year simulation was done to compare the following four climate conditions: (1) no change (i.e., continuous input of the daily weather data and [CO₂] from 2001), (2) [CO₂] change (i.e., continuous input of the daily weather data from 2001 but [CO₂] increased as defined by the RCP), (3) air temperature change (i.e., continuous input of [CO₂] from 2001 but temperature changes based on the GCMs), and (4) simultaneous [CO₂] and air temperature change (i.e., the normal simulation).

To examine the sensitivity of the response of SOC storage in the top 30 cm of the soil, aboveground rice biomass, and CH₄ emission to different decomposition rates for the soil humus fraction [i.e., 1.0× (DNDC-Rice's default), 0.8×, 0.7× (the rate used in the present study), 0.6×, and 0.4×], we also performed a sensitivity analysis for the CF practice at the Suphan Buri site under RCP4.5.

3. Results and discussion

3.1. Performance of the adjusted model

The adjusted model based on the observed rice heading and maturation dates at each site did a good job of reproducing the observed rice grain yield and CH₄ emission (Fig. 2). The fit for grain yield ($R^2 = 0.99$, NRMSE = 0.11; Fig. 2a) were better than those in our previous multi-site simulation in Japan ($R^2 = 0.22$, NRMSE = 0.17; Minamikawa et al., 2014). The tendency toward underestimation in the previous study was therefore mitigated by the new crop submodel deployed in the present study. The fit for CH₄ emission ($R^2 = 0.96$, NRMSE = 0.29; Fig. 2b) was improved compared with those in previous multi-site simulations in

1 Thailand ($R^2 = 0.36$, NRMSE = 0.72; Smakgahn et al., 2009) and Japan ($R^2 = 0.74$, NRMSE =
2 0.49; Minamikawa et al., 2014). Smakgahn et al. (2009) reported poor estimation of rice root
3 biomass with a different crop submodel (see Table S1). In DNDC-Rice, the rice root biomass
4 determines the amount of rhizodeposition that is used as carbon substrates for CH₄ production
5 (Fumoto et al., 2013). On the other hand, Minamikawa et al. (2014) reported overestimation
6 of CH₄ emission due to limitations in the model's description to calculate daily CH₄ emission
7 on the day of soil reflooding after the drained periods, which had been modified in version 3.0
8 of DNDC-Rice.

9 There were two outliers in the model's performance. At the Ratchaburi site, one plot used
10 an organic amendment (conventional application of chemical fertilizers + *Sesbania rostrata* at
11 a rate of 30 t ha⁻¹ fresh weight), and the rice grain yield (3120 kg ha⁻¹) was much lower than
12 that simulated by the adjusted model (4320 kg ha⁻¹; Fig. 2a). Although Jermasawadipong et al.
13 (1994) did not explicitly mention the reason for this yield reduction compared with the
14 chemical fertilizer plot (3600 kg ha⁻¹), we hypothesize that this was caused by organic acids
15 produced due to the high input of organic matter at once (~3000 kg C ha⁻¹). DNDC-Rice is
16 not able to account for the negative effect of such extreme soil conditions on rice growth.
17 However, this was not a problem in our subsequent long-term simulation because the
18 incorporation rate of rice straw was closer to the normal level (see Fig. S1). The second
19 outlier was a relatively high CH₄ emission at the Suphan Buri site (75 g CH₄ m⁻²) that was not
20 well reproduced by the model (51.2 g CH₄ m⁻²; Fig. 2b). This is mainly because of the limited
21 frequency of field observations in this study (i.e., only three times in the latter growth stage;
22 Yagi et al., 1994). The mean of the high CH₄ fluxes observed was used to calculate the
23 seasonal cumulative emission, thereby causing an overestimation. Therefore, based on the low
24 number of outliers and the ability to explain them as the result of abnormal conditions not
25 accounted for by DNDC-Rice, we conclude that the adjusted model for each site is suitable

for use in the subsequent long-term simulation.

3.2. Long-term simulation under the different scenarios

3.2.1. Characteristics of the generated climate parameters

Annual mean or total values of the generated climate parameters differed slightly among the four meteorological stations (Table 2). All the parameters at the start of the simulation period (i.e., 2001 to 2010) were similar among the four RCPs at each station. The annual mean daily maximum and minimum air temperatures at the end of the simulation period (i.e., 2051 to 2060) were higher than those at the start of the simulation period at all stations and all RCP scenarios, but also generally had a larger 95% CI among the seven GCMs. Air temperatures in RCP4.5 at the end of the simulation period were marginally higher than those in RCP6.0 at all stations, in accordance with the higher [CO₂] of RCP4.5 (see section 2.4.2). The annual total precipitation was marginally greater at the end of the simulation period under almost all situations. The annual mean daily solar radiation was comparable between the start and end of the simulation period.

3.2.2. Effect of water management on CH₄ emission

The effect of water management on the simulated CH₄ emission was consistent throughout the 60-year simulation (Fig. 3). Although there were often overlaps of the 95% CIs among the seven GCMs between the water management practices, the simulated CH₄ emission was always in the following order: CF > SA > MA. The potential mitigation of CH₄ emission by SA and MA relative to CF (i.e., the percentage of CH₄ emission reduction compared to that from CF) was generally comparable among the four RCPs and between the start and end of the simulation period at each site, except for the MA at the Pathum Thani and

1 **Suphan Buri sites** (Table 3). In addition, the mean CH₄ emission from SA at the end of the
2 simulation period was smaller than that from CF at the start of the simulation period under all
3 situations.

4 **The above results suggest that climate change will not weaken the mitigation potential**
5 **during the simulation period.** This can be explained by two reasons. First, there was a
6 relatively small difference in climate conditions at the end of the simulation period among the
7 four RPCs and even between the start and end of the simulation period at each site (Table 2).
8 Thus, the pattern of seasonal variation in CH₄ flux under CF was similar throughout the
9 simulated years at each site (see Fig. S2 for examples). Second, we used the same timing of
10 the drainage periods in the fixed crop calendar throughout the simulation period at each site,
11 so the water regime played a consistent role as a mitigator of CH₄ under any combination of
12 climate and environmental conditions.

13 Among the six sites, the mitigation potential by SA and MA was highest at Samut Sakhon
14 and lowest at Pathum Thani (Table 3). In contrast, the magnitude of CH₄ emission from CF
15 was lowest at Samut Sakhon and highest at Pathum Thani (Fig. 3). In a 2-year multi-site
16 monitoring study in Japan, Itoh et al. (2011) reported that the mitigation potentials of CH₄
17 emission by the water management practices, similar in timing and duration to those in the
18 present study, varied spatially and temporarily because of the different patterns of seasonal
19 variation. The spatial variability of the mitigation potential in the present study appears to
20 stem from the differences in the potential CH₄ production. In accordance with the results of
21 Itoh et al. (2011), we found that the mitigation potential **increased** when active CH₄
22 production and emission occurred **red** in CF during periods corresponding to the drainage for SA
23 and MA, and vice versa (see Fig. S3 for examples).

24 The regional mean potential mitigation by SA and MA relative to CF at the start of the
25 simulation period were 22.0 to 22.5% and 52.5 to 52.8%, respectively, regardless of the RCP

scenario (Fig. 4), and these ranges were similar to those at the end of the simulation period (21.9 to 22.9% for SA and 53.5 to 55.2% for MA). These values were within the error range of the IPCC (2006) scaling factor for water regime with SA (20 to 54%, after conversion to the same units) and with MA (34 to 59%). The relatively weak mitigation potential of SA in the present study can be partly explained by the random effect of precipitation during the drainage periods, as observed by Kim et al. (2016). This is especially true because the present study included a simulation in the rainy season as well as the dry season. Minamikawa et al. (2014) also reported that the simulated mean mitigation potential by several kinds of SA in nine rice paddies distributed across Japan ($20.1 \pm 5.6\%$) was lower than the observed mean ($30.5 \pm 6.7\%$; Itoh et al., 2011). We therefore recognize that the simulated mitigation potentials in the present study would reflect variation due to normal (i.e., not always fine) weather conditions.

3.2.3. Effect of climate change on the increase in CH_4 emission

The simulated CH_4 emission gradually increased during the simulation period, and the magnitude of the increase depended on the RCP scenario (Fig. 3). The simulated CH_4 emission from CF at the end of the simulation period was 5.3 to 7.8%, 9.6 to 16.0%, 7.3 to 18.0%, and 13.6 to 19.0% greater than those at the start of the simulation period in the RCPs 2.6, 4.5, 6.0, and 8.5, respectively (Table 3). The magnitude of the increases in SA and MA were comparable to those in CF, except for MA at the Pathum Thani and Ratchaburi sites.

Figure 5 shows the response of SOC storage in the top 30 cm of the soil, harvested rice aboveground biomass, and CH_4 emission to the changing climate conditions for CF at Suphan Buri under RCP4.5. The SOC storage was positively affected by the change in $[CO_2]$ due to the increased amount of post-harvest straw incorporation (Fig. 5ab). The change in air temperature had a negative effect on rice biomass production (Fig. 5b). Compared with the

mean CH₄ emission at the end of the simulation period for the no-change scenario, emission was 12.7% higher for [CO₂] change, 1.3% higher for air temperature change, and 12.5% higher for [CO₂] + air temperature change (Fig. 5c). This suggests the importance of [CO₂] change for the increase in CH₄ emission, through the role of rice plants as a supplier of metabolic substrates as well as providing an emission pathway through the rice plant's aerenchyma. However, as reported by Banger et al. (2015), a longer simulation may predict negative effects of climate change on rice growth and CH₄ emission due to a higher temperature rise.

So far as we know, there has been no previous report on the combined effects of climate change and water management on paddy CH₄ emission. Tokida et al. (2010) reported the results of a 2-year CH₄ emission study in continuously flooded rice paddies in Japan (39°38'N) under a FACE treatment (i.e., ambient [CO₂] + 200 ppmv), elevated soil temperature (+2°C), and a combination of the two. Climate conditions at the end of the simulation period in RCP8.6 (Table 2) were closest to their study conditions. The combined effect of FACE and soil warming on the increase in CH₄ emission was about 80%, whereas the magnitude of the increase in CF at the end of the simulation period in RCP8.6 in the present study was 13.6 to 19.0% among the six sites (Table 3). The independent effects of FACE and soil warming on the emission increase were 26 and 44%, respectively (Tokida et al., 2010). A largest environmental difference between our study sites and Tokida et al.'s study site is a change of climatic zone, from tropical in Thailand (south of 15°11'N, Table 1) to cool-temperate in Japan. We should also note that the experimental conditions of Tokida et al. (2010) were distinctly different from the assumptions and scenarios in the present study: they returned no rice straw to the soil, and warmed the soil during the rice growing season only. As no rice straw was returned to the soil, rice plant would have made relatively large contribution to CH₄ production in the soil. Furthermore, they observed significant increase in rice biomass

1 by soil warming, presumably due to enhanced SOC decomposition and N mineralization
2 during the rice growing season. These factors probably contributed to the increase of as much
3 as 44% in CH₄ emission as the independent effect of soil warming.

4 A recent meta-analysis by van Groenigen et al. (2013) indicated that increased [CO₂]
5 (ranging from 550 to 743 ppmv) increased paddy CH₄ emission by an average of 42.2%, but
6 that there was no evidence of an effect of air or soil warming (ranging from +0.8°C to +6.0°C).
7 These results are consistent with our simulation results under the manipulated climate
8 conditions (Fig. 5c). Van Groenigen et al. (2013) suggested that the effect of warming on CH₄
9 production was positive at relatively low ambient temperatures, but was smaller or became
10 negative under relatively warm ambient temperatures. The latter conditions would be true of
11 our study sites in central Thailand and the former Tokida et al.'s site in Japan. In addition, the
12 relatively small effect of climate change on the increase in CH₄ emission in the present study
13 can be partly explained by the decrease of SOC storage, as we will discuss in section 3.3.
14 Tokida et al. (2010) argued that their soil warming might have resulted in overestimation of
15 CH₄ production from SOC because the amount of labile SOC did not differ among the plots at
16 the start of the warming treatment. Under real climate change, SOC storage would gradually
17 decrease due to accelerated decomposition.

18 Xie et al. (2012) reported the results of a 4-year CH₄ emission study in intermittently
19 drained rice paddies in China (32°35'N) under a FACE treatment (i.e., ambient [CO₂] + 200
20 ppmv). Their water management practice was similar to MA in the present study. The FACE
21 treatment increased CH₄ emission by an average of 15% (Xie et al., 2012). Although the
22 authors did not explicitly describe this possibility, we hypothesize that the relatively small
23 increase resulted at least partially from the effect of their water management. That is, the
24 FACE effect on CH₄ emission would have been masked by the drainage practices starting
25 from 30 days after transplanting, which greatly decreased CH₄ production and emission

without regard to [CO₂]. This masking effect may explain the smaller climate-change effects of MA at the Pathum Thani and Ratchaburi sites (Table 3).

3.3. Limitations and implications of the present study

In the present study, we made several assumptions about SOC dynamics and field management practices for the long-term simulation of CH₄ emission. As we noted in section 2.3, we used a lower decomposition rate of the soil humus fraction than the default value to account for the results of long-term field monitoring of SOC in the same region of the tropics (Pampolino et al., 2008). To confirm the reliability of our simulation results, we performed a sensitivity analysis for the SOC storage, harvested rice biomass, and CH₄ emission using different decomposition rates for the humus fraction (Fig. 6). In DNDC-Rice, humus is the most abundant fraction in the conceptual SOC pool. Figure 6a shows that SOC storage was strongly affected by the decomposition rate; storage increased at the lowest decomposition rates and decreased at the highest rates. However, the responses of rice aboveground biomass and CH₄ emission did not differ significantly among the decomposition rates (Fig. 6bc). The latter results can be explained by the importance of labile fractions of carbon and nitrogen in plant development and CH₄ production in the DNDC-Rice model (Fumoto et al., 2008, 2010). Our sensitivity analysis confirmed that the simulated CH₄ emissions are not sensitive to changes in the decomposition rate of the soil humus fraction.

We assumed the incorporation of all the rice straw into the soil after harvesting of both crops to preserve the SOC storage. However, this assumption caused greater simulated CH₄ emission than that observed in the field experiment at all sites. In a nationwide estimation of CH₄ emission from rice paddies in Japan using version 1.2 of DNDC-Rice (Table S1), Katayanagi et al. (2016) also found a significant positive correlation between the simulated

CH₄ emission and the amount of organic carbon input to the field. Given that this is the case, how should we balance the need to preserve SOC storage with the resulting increase in CH₄ emission? Yu et al. (2013) projected that SOC storage in the top 30 cm of the soil under rice-based cropping systems in southern China will gradually decrease during the next four decades without intensive field management practices to restore SOC. **Therefore, it is necessary to investigate an optimum level of SOC storage for harmonizing climate change mitigation and adaptation in the future research.**

We did not examine rice productivity in our long-term simulation. Because a series of input parameters for rice cultivation (e.g., cultivar, fertilizer) were usually obtained under the specific conditions of a previous single experiment (see Table 1), such settings would not necessarily reflect future conditions. Although version 3.0 of DNDC-Rice performed **relatively well with calibration only for rice phenology** in predicting rice growth under current climate conditions (Li et al., 2015), it will be necessary to validate DNDC-Rice using detailed rice growth data under manipulated climate conditions to allow prediction of rice productivity under future climate conditions.

4. Conclusions

We performed a series of long-term simulations using the DNDC-Rice model to test the hypothesis that an appropriate water management practice could mitigate the predicted increase in CH₄ emission from irrigated rice paddies that will occur under future climate conditions. We confirmed our hypothesis based on a case study using data from six sites in central Thailand. The potential mitigation of CH₄ emission by SA and MA relative to CF was consistent among various climate change scenarios. The regional mean mitigation potentials by SA and MA relative to CF at the end of the simulation period (i.e., 2051 to 2060) were

21.9 to 22.9% and 53.5 to 55.2%, respectively, regardless of the RCP scenario, which were comparable to those at the start of the simulation period (i.e., 2001 to 2010). The results indicate that near-future climate change will not attenuate the effect of water management practices on mitigating CH₄ emission from irrigated rice paddies in central Thailand. In addition, the results suggest that adopting SA can keep CH₄ emission at the end of the simulation period at a level less than that under CF at the start of the simulation period. Therefore, appropriate water management practices may mitigate concerns over positive feedbacks between climate change on CH₄ emission (Tokida et al., 2010).

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1 **Figures and Tables**

2

3 **Fig. 1.** Locations of the six experimental sites and of the Bang Na meteorological station in

4 central Thailand.

Fig. 2. Relationship between observed and simulated values for (a) rice grain yield and (b) CH₄ emission at the six experimental sites. The solid black line indicates the result of linear regression. The y-intercept did not differ significantly from zero ($P > 0.05$), so the regression was constrained to have a y-intercept of zero. Only for the Samut Sakhon site, vertical gray bar indicates the standard deviation of observed value.

Fig. 3. Interannual variation in the simulated CH_4 emission at the six experimental sites for the three water management practices during the simulation period from 2001 to 2060 under the four RCP scenarios. The solid line for each water management practice represents the mean among the seven GCMs, and the corresponding shaded area represents the 95% CI.

Fig. 4. The potential mitigation of CH₄ emission by single aeration (SA) and multiple aeration (MA) relative to the emission under continuous flooding in central Thailand at the start (2001 to 2010) and end (2051 to 2060) of the simulation period under the four RCP scenarios. Values represent the mean among the six experimental sites and the corresponding 95% CI.

Fig. 5. Response of (a) SOC storage in the top 30 cm of the soil, (b) harvested rice aboveground biomass, and (c) CH₄ emission to the changing climate conditions at the Suphan Buri site under continuous flooding in the RCP4.5 scenario. The solid line represents the mean among the seven GCMs and the shaded area represents the corresponding 95% CI. Treatments: No, no change in [CO₂] or air temperature (T); [CO₂], change in [CO₂] alone; T, change in T alone; [CO₂] + T, both changes in [CO₂] and T. See section 2.4.3 for details of each manipulation.

Fig. 6. Response of (a) SOC storage in the top 30 cm of the soil, (b) harvested aboveground biomass, and (c) CH_4 emission to different decomposition rates for the soil humus fraction [1.0 $\times$ (DNDC-Rice's default), 0.8 $\times$, 0.7 $\times$ (the rate used in the present study), 0.6 $\times$, and 0.4 $\times$] at the Suphan Buri site under continuous flooding in the RCP4.5 scenario. The solid line represents the mean among the seven GCMs and the corresponding shaded area represents the 95% CI. Note that the lines in (b) and (c) overlap each other.

Table 1

Basic information on the six study sites and the adjusted input parameters for DNDC-Rice.

Site	Chai Nat	Suphan Buri	Khlong Luang	Pathum Thani	Samut Sakhon	Ratchaburi
Latitude and longitude	15°11'N/100°8'E	14°28'N/100°5'E	14°2'N/100°49'E	14°1'N/100°43'E	13°37'N/100°19'E	13°29'N/99°47'E
Study year	1991 ^a	1991 ^a	1991 ^a	1992 ^b	2002 ^c and 2007 ^d	1992 ^b
Soil taxonomy	Aeric Tropaquept	Vertic Tropaquept	Sulfic Tropaquept	Thionic Tropaquept	Typic Tropaquept	Fulvic Tropaquept
Soil C and N (%)	0.9/0.08	1.3/0.10	1.2/0.10	2.35/0.18	1.15/0.18	1.02/0.07
Soil pH	5.2	6.1	4.3	4.0	6.1	7.1
N fertilization rate (kg N ha ⁻¹ season ⁻¹)	80	80	80	35	69	50
Dry-season calendar ^e						
Plowing	<i>19 Feb.</i>	17 Jan.	19 Feb.	<i>17 Jan.</i>	8 Apr.	<i>17 Jan.</i>
Transplanting	<i>28 Feb.</i>	7 Feb.	28 Feb.	<i>7 Feb.</i>	13 Apr.	<i>7 Feb.</i>
Basal fertilization	<i>7 Mar.</i>	19 Feb.	7 Mar.	<i>19 Feb.</i>	8 May	<i>19 Feb.</i>
Top-dressing	<i>9 Apr.</i>	27 Mar.	9 Apr.	<i>27 Mar.</i>	8 Jun.	<i>27 Mar.</i>
Harvest	<i>30 May</i>	20 May	30 May	<i>20 May</i>	1 Aug.	<i>20 May</i>
Rainy-season calendar ^e						
Plowing	19 Aug.	8 Aug.	<i>19 Aug.</i>	24 Jul.	15 Aug.	4 Aug.
Transplanting	23 Aug.	23 Aug.	<i>23 Aug.</i>	5 Aug.	6 Sep.	14 Aug.
Basal fertilization ^f	22 Aug.	3 Sep.	<i>22 Aug.</i>	29 Jul.	26 Sep.	13 Aug.
Top-dressing	12 Sep.	3 Oct.	<i>12 Sep.</i>	15 Sep.	26 Oct.	23 Sep.
Harvest	5 Dec.	28 Nov.	<i>5 Dec.</i>	18 Nov.	25 Dec.	26 Nov.
Reducible Fe content (mol kg ⁻¹)	0.1362	0.0967	0.1417	0.1098	0.1081	0.0668
Vegetative growth rate constant (d ⁻¹)	0.027	0.027	0.027	0.030	0.027	0.030
Reproductive growth rate constant (d ⁻¹)	0.009	0.009	0.010	0.008	0.011	0.085

^a Yagi et al. (1994); ^b Jermsawatdipong et al. (1994); ^c Towprayoon et al. (2005); ^d Jiaphasuanan and Towprayoon (2014).

^e Italics indicate that the date was obtained from a neighboring site due to a lack of observations at the study site.

^f Basal fertilization was often performed before transplanting in the rainy season.

Table 2

Generated climate parameters at the four meteorological stations under the four RCP scenarios at the start (2001 to 2010) and end (2051 to 2060) of the simulation period.

Station	Chai Nat		Suphan Buri		Bang Na		Ratchaburi	
Decade	Start	End	Start	End	Start	End	Start	End
Annual mean daily maximum air temperature (°C)								
RCP2.6	34.2 ± 0.3	35.0 ± 0.4	33.9 ± 0.4	34.5 ± 0.3	33.3 ± 0.2	34.0 ± 0.3	33.6 ± 0.1	34.3 ± 0.3
RCP4.5	34.1 ± 0.2	35.3 ± 0.3	33.8 ± 0.4	35.0 ± 0.3	33.3 ± 0.2	34.5 ± 0.2	33.6 ± 0.2	34.8 ± 0.2
RCP6.0	34.2 ± 0.2	35.2 ± 0.6	33.8 ± 0.4	34.6 ± 0.4	33.3 ± 0.2	34.2 ± 0.3	33.6 ± 0.1	34.4 ± 0.3
RCP8.5	34.2 ± 0.3	35.9 ± 0.8	33.8 ± 0.4	35.4 ± 0.5	33.3 ± 0.2	35.0 ± 0.5	33.6 ± 0.1	35.1 ± 0.5
Annual mean daily minimum air temperature (°C)								
RCP2.6	23.8 ± 0.2	24.6 ± 0.3	24.1 ± 0.2	24.8 ± 0.3	24.9 ± 0.1	25.7 ± 0.3	23.7 ± 0.1	24.4 ± 0.3
RCP4.5	23.8 ± 0.2	25.0 ± 0.4	24.0 ± 0.2	25.2 ± 0.4	24.9 ± 0.1	26.1 ± 0.4	23.6 ± 0.1	24.8 ± 0.4
RCP6.0	23.7 ± 0.2	24.7 ± 0.3	24.0 ± 0.2	24.9 ± 0.3	24.8 ± 0.1	25.7 ± 0.3	23.6 ± 0.1	24.5 ± 0.3
RCP8.5	23.8 ± 0.2	25.6 ± 0.5	24.0 ± 0.2	25.8 ± 0.5	24.9 ± 0.1	26.6 ± 0.5	23.6 ± 0.1	25.4 ± 0.5
Annual total precipitation (mm y ⁻¹)								
RCP2.6	1063 ± 74	1050 ± 70	979 ± 62	1011 ± 87	1471 ± 67	1507 ± 121	1139 ± 43	1183 ± 97
RCP4.5	1069 ± 60	1140 ± 59	994 ± 59	1103 ± 80	1487 ± 70	1606 ± 96	1153 ± 43	1270 ± 90
RCP6.0	1064 ± 46	1054 ± 94	999 ± 31	1013 ± 82	1499 ± 42	1513 ± 114	1163 ± 36	1177 ± 111
RCP8.5	1059 ± 79	1131 ± 62	984 ± 71	1067 ± 66	1473 ± 69	1564 ± 73	1140 ± 44	1237 ± 79
Annual mean daily solar radiation (MJ m ⁻² d ⁻¹)								
RCP2.6	19.1 ± 0.3	19.4 ± 0.2	18.6 ± 0.2	18.8 ± 0.3	18.2 ± 0.2	18.4 ± 0.2	17.9 ± 0.1	18.2 ± 0.2
RCP4.5	19.2 ± 0.2	19.3 ± 0.1	18.6 ± 0.2	18.7 ± 0.2	18.3 ± 0.2	18.4 ± 0.1	18.0 ± 0.1	18.1 ± 0.2
RCP6.0	19.1 ± 0.2	19.1 ± 0.2	18.6 ± 0.2	18.6 ± 0.2	18.3 ± 0.2	18.2 ± 0.2	18.0 ± 0.1	17.9 ± 0.2
RCP8.5	19.2 ± 0.2	19.2 ± 0.1	18.7 ± 0.1	18.6 ± 0.2	18.3 ± 0.1	18.2 ± 0.2	18.0 ± 0.1	17.9 ± 0.2

Value indicates the mean among the seven GCMs and its 95% CI.

Table 3

Comparison of the mean simulated CH₄ emission among the three water management practices at the six experimental sites under the four RCP scenarios at the start (2001 to 2010) and end (2051 to 2060) of the simulation period.

	Start		End		End/Start (%)		
	SA/CF (%)	MA/CF (%)	SA/CF (%)	MA/CF (%)	CF	SA	MA
Chai Nat							
RCP2.6	79.1 ± 1.0	51.5 ± 1.0	78.3 ± 1.3 (84.4 ± 2.4)	49.2 ± 1.7 (53.0 ± 2.2)	107.8 ± 2.7	106.8 ± 3.3	103.0 ± 3.9
RCP4.5	78.8 ± 1.0	51.5 ± 1.3	79.4 ± 1.0 (89.9 ± 2.0)	51.3 ± 2.2 (58.1 ± 2.8)	113.2 ± 1.8	114.0 ± 2.7	113.0 ± 3.1
RCP6.0	79.3 ± 1.2	51.4 ± 1.6	79.4 ± 1.5 (89.1 ± 2.9)	50.7 ± 2.6 (57.0 ± 3.4)	112.2 ± 1.8	112.4 ± 2.8	110.8 ± 4.0
RCP8.5	78.6 ± 1.3	50.8 ± 1.7	78.8 ± 2.0 (92.0 ± 3.2)	50.0 ± 3.1 (58.3 ± 4.2)	116.8 ± 1.4	117.0 ± 2.2	114.8 ± 5.0
Suphan Buri							
RCP2.6	80.7 ± 1.3	51.8 ± 0.4	79.4 ± 0.8 (85.6 ± 1.8)	49.4 ± 1.4 (53.2 ± 2.0)	107.8 ± 2.3	106.1 ± 3.1	102.8 ± 4.2
RCP4.5	81.1 ± 1.2	52.1 ± 0.6	79.9 ± 0.6 (90.1 ± 2.2)	50.0 ± 1.3 (56.4 ± 2.3)	112.7 ± 3.3	111.2 ± 3.1	108.2 ± 4.5
RCP6.0	80.5 ± 1.1	51.9 ± 1.1	79.7 ± 0.5 (89.1 ± 2.1)	50.0 ± 1.3 (55.9 ± 1.1)	111.8 ± 3.0	110.7 ± 2.3	107.8 ± 2.2
RCP8.5	80.6 ± 1.2	51.7 ± 0.9	80.6 ± 0.4 (94.4 ± 2.3)	51.1 ± 1.8 (59.9 ± 2.7)	117.2 ± 2.5	117.2 ± 3.3	115.9 ± 5.6
Khlong Luang							
RCP2.6	79.5 ± 0.8	48.4 ± 2.1	79.3 ± 1.6 (84.7 ± 1.7)	46.4 ± 2.7 (49.5 ± 2.6)	106.7 ± 2.0	106.5 ± 2.0	102.3 ± 2.4
RCP4.5	78.8 ± 1.5	48.2 ± 2.4	79.2 ± 2.2 (89.9 ± 4.1)	49.5 ± 4.1 (56.2 ± 3.7)	113.5 ± 3.3	114.1 ± 4.9	116.6 ± 3.8
RCP6.0	79.5 ± 1.0	48.4 ± 2.0	79.5 ± 1.4 (89.9 ± 2.8)	47.1 ± 2.5 (53.3 ± 2.4)	113.1 ± 2.9	113.1 ± 3.8	110.0 ± 4.5
RCP8.5	79.5 ± 1.2	48.6 ± 2.4	81.2 ± 2.1 (96.5 ± 4.7)	49.8 ± 3.1 (59.3 ± 4.8)	119.0 ± 3.4	121.4 ± 6.2	122.0 ± 9.8
Pathum Thani							
RCP2.6	86.6 ± 0.9	55.2 ± 0.9	86.5 ± 1.1 (93.0 ± 2.3)	51.1 ± 0.9 (55.0 ± 1.0)	107.5 ± 2.3	107.4 ± 2.6	99.6 ± 2.5
RCP4.5	86.7 ± 1.0	55.2 ± 0.8	86.4 ± 0.9 (96.5 ± 2.1)	51.6 ± 1.5 (57.7 ± 1.9)	111.8 ± 1.6	111.4 ± 1.5	104.5 ± 2.5
RCP6.0	86.9 ± 1.1	54.9 ± 1.5	86.3 ± 0.7 (95.5 ± 2.4)	51.0 ± 2.0 (56.4 ± 2.6)	110.6 ± 2.8	110.0 ± 3.0	102.7 ± 4.1
RCP8.5	87.0 ± 1.0	55.2 ± 1.2	86.2 ± 0.9 (99.6 ± 2.2)	51.1 ± 1.5 (59.0 ± 1.9)	115.5 ± 1.9	114.4 ± 2.0	106.9 ± 2.7
Samut Sakhon							
RCP2.6	65.1 ± 5.7	30.7 ± 3.9	65.9 ± 4.9 (70.0 ± 7.4)	29.7 ± 4.0 (31.5 ± 5.2)	106.2 ± 6.0	107.5 ± 6.3	102.5 ± 8.7
RCP4.5	67.2 ± 3.9	32.4 ± 1.4	68.6 ± 5.1 (79.6 ± 8.1)	32.4 ± 2.7 (37.7 ± 3.9)	116.0 ± 4.0	118.5 ± 7.1	116.1 ± 11.0
RCP6.0	68.0 ± 4.3	32.9 ± 3.3	66.5 ± 5.0 (78.4 ± 6.0)	31.1 ± 2.5 (36.7 ± 2.4)	118.0 ± 6.6	115.4 ± 7.0	111.5 ± 10.9
RCP8.5	67.2 ± 4.8	33.0 ± 3.7	67.5 ± 4.6 (78.7 ± 6.3)	31.5 ± 3.3 (36.7 ± 4.3)	116.7 ± 7.2	117.2 ± 8.8	111.4 ± 14.0
Ratchaburi							
RCP2.6	73.9 ± 1.7	45.3 ± 1.1	73.1 ± 0.7 (76.9 ± 1.3)	43.1 ± 1.1 (45.3 ± 1.1)	105.3 ± 1.6	104.0 ± 2.6	100.0 ± 3.0
RCP4.5	73.9 ± 1.5	45.5 ± 1.2	74.0 ± 0.7 (81.1 ± 1.9)	43.9 ± 1.3 (48.1 ± 1.8)	109.6 ± 2.0	109.7 ± 1.9	105.6 ± 3.0
RCP6.0	74.0 ± 1.3	45.7 ± 1.2	74.2 ± 1.2 (79.6 ± 1.7)	43.5 ± 1.7 (46.7 ± 1.9)	107.3 ± 1.5	107.5 ± 2.5	102.2 ± 3.5
RCP8.5	73.8 ± 1.3	45.2 ± 1.2	74.3 ± 0.9 (84.4 ± 1.7)	43.6 ± 1.7 (49.5 ± 1.9)	113.6 ± 1.9	114.4 ± 2.5	109.5 ± 3.8

CF, continuous flooding; SA, single aeration; and MA, multiple aeration.

Values are for the mean among the seven GCMs and the corresponding 95% CI.

Values in parentheses represent a comparison with CF at the start of the simulation period.

GRAPHICAL ABSTRACT