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The Effect of Water Management and Ratoon Rice Cropping on Methane Emissions and Harvest Yield in Arkansas

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The Effect of Water Management and Ratoon Rice Cropping on Methane Emissions and Harvest Yield in Arkansas

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Abstract

Sustainable intensification of rice farming is crucial to meeting human food needs while reducing environmental impacts. Rice produces 8% of all anthropogenic CH_4, which is a potent greenhouse gas. CH_4 emissions can potentially be reduced by cultivation practices that minimize the number of days the fields are saturated, such as dry-seeding instead of water-seeding and irrigation using the alternate wetting and drying (AWD) technique instead of delayed, continuous flooding (DF). Ratoon cropping, wherein a second crop of rice is grown from the harvested stubble of the first crop, can be used to produce additional yield with minimal labor, but may generate more CH_4 than single cropping. The objective of this study was to test different seeding methods and water management regimes for their impact on yield and CH_4 emissions, as well as to determine if ratoon cropping was a viable method of sustainable intensification for rice in Arkansas. Adjacent fields in Lonoke County, Arkansas were compared under different seeding and irrigation treatments from 2015 through 2020; the 2020 season also included a ratoon crop. Field-scale CH_4 emissions were measured using the eddy covariance method at each field. AWD reduced CH_4 emissions by 79.5% on average in comparison to DF for the main seasons. CH_4 emissions from the main crop ranged from 11.0 to 40.7 kg ha^{-1}, while CH_4 emissions from the ratoon crop ranged from 39.7-50.7 kg ha^{-1}, up to a 3.6-fold increase in emissions relative to the main crop. CH_4 emissions from the ratoon crop in this study were much lower than those found in previous ratoon studies, suggesting that ratoon cropping combined with AWD might be a viable option for sustainable intensification if the ratoon yield could be improved. The ratoon crop yield was 13% that of the main crop yield on average but there was no significant difference in yield between treatments for the main seasons. Seeding method had no discernable impact on CH_4 emissions or yield.

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1. Introduction

Rice is a staple crop, with about 480 million tons produced worldwide each year (Muthayya et al., 2014). While the majority of rice is produced in Asia, the United States produces 5-6% of global exports, most of which is grown in Arkansas and California (Childs, 2021). Rice is responsible for 8% of anthropogenic CH_4 emissions, due to the flooded, anaerobic conditions under which it is usually grown, and crops in general are a significant atmospheric source of N_2O and CO_2 (Ciais et al., 2013; Cole et al., 1997; Saunois et al., 2020).

Meanwhile, climate change threatens global food security, as it is expected to increase the magnitude and duration of severe weather events, leading to floods, droughts, and crop damage (Meehl et al., 2000). While an extended growing season and increased atmospheric CO_2 can be beneficial to plant growth, the increased plant stress associated with higher temperatures could negate the potential benefits (Mbow et al., 2019). Water scarcity and the prevalence of plant pathogens and pests are also likely to become larger problems, stressing crops further (Dukes et al., 2009; Mbow et al., 2019; Meehl et al., 2000). The result is an agricultural system of unpredictable productivity in a world of increasing population, which makes sustainable intensification crucial.

Different rice seeding methods may influence the environmental impact of the rice crop. Rice seeding methods in the United States are divided into water seeding and dry seeding. Water seeding is a direct seeding method where pre-germinated rice is broadcast usually from a plane, onto a moist or inundated field. Dry seeding is a direct seeding method where rice is drill seeded or broadcast onto a dry field. Water seeding is common in Texas, South Louisiana, and California because it suppresses weedy red rice and requires less labor (Saichuk, 2014). It is less common in Arkansas, where it makes up only 6% of seed establishment methods (Hardke, 2018).

Water-seeded rice can produce greater CH_4 emissions across a season than dry seeded rice (Hang et al., 2014; Ko & Kang, 2000; Tao et al., 2016). This increase is generally regarded as a direct result of irrigation treatment, as the flooded conditions necessary during the planting period for water seeded rice result in a longer period of anaerobic conditions (Hang et al., 2014; Y. Jiang et al., 2017). Dry seeded rice has been shown to produce higher N_2O emissions, since N_2O is produced preferentially under aerobic conditions, but the overall global warming potential (GWP) of water seeded rice is still greater (Gupta et al., 2016; Hang et al., 2014; Tao et al., 2016).

Within the growing season, irrigation management practices have great potential to reduce CH_4 emissions by decreasing the total duration of field inundation. The alternate wetting and drying (AWD) practice, where rice fields are flooded and then periodically allowed to dry down before reflooding, significantly reduces CH_4 emissions compared to delayed, continuous flooding (Balaine et al., 2019; LaHue et al., 2016; Linquist et al., 2015, 2018; Runkle et al., 2019). Longer drying periods show greater reductions in emissions, although long drying periods could also decrease the yield (Balaine et al., 2019; Carrijo et al., 2017; Linquist et al., 2015). Given the possibility of yield loss, moderate drying periods may provide the best balance between reducing GHG emissions and producing a profitable harvest.

Some of the anticipated yield loss associated with climate change could be mitigated by ratoon cropping. This practice induces the growth of a second crop from the harvested stubble of the first crop by flooding and fertilizing the stubble. It has been practiced in India, China, the USA, the Philippines, Brazil, Colombia, Thailand, Taiwan, and the Dominican Republic

(Cuevas-Pérez, 1988; Krishnamurthy, 1988). Ratoon rice fell out of common use in many countries after the 1950's (Mahadevappa, 1988; Torres et al., 2020; Yuan et al., 2019) because it did not always deliver a consistent yield. The ratoon yield could range from 6 to 63% that of the main crop on the same field in different years (Andrade et al., 1988). It remained a commercial practice only in parts of Texas and Louisiana and in the Dominican Republic (Harrell et al., 2009; Mahadevappa, 1988; Yuan et al., 2019).

Recently, however, ratoon cropping has seen a resurgence, as the rise in mechanized farming, better management techniques, and improved rice cultivars have reduced the labor required and increased the expected yield. In the United States alone, ratoon cropping covers 37% of rice grown in Louisiana and 53% of rice grown in Texas (Harrell, 2020; Wilson et al., 2020). Ratoon cropping is a useful practice in areas where the growing season is long enough to allow it, as the farmer gets additional yield without much extra investment since very little labor is involved in managing the ratoon crop (Santos et al., 2003). It can also salvage part of a crop damaged by lodging or drought stress, an important consideration in a world increasingly prone to drought (Torres et al., 2020). Even if the season is not long enough for the ratoon crop to reach maturity, the regrowth can be used as forage (Dong et al., 2020).

Previously ratoon cropping was only possible in limited areas due to the long growing season needed to bring the regenerated crop to maturity. Now that global temperatures have risen, the growing season has been extended, making ratoon cropping possible in areas that were previously too cold for it (Ziska et al., 2018). This practice could be an efficient way to increase yield, but the environmental impact needs to be evaluated. Due to the extended flooding period and the large amount of fresh crop residue remaining on the field after the initial harvest, ratoon cropping may have a greater GWP than single cropping. Ratoon crops often emit from two to four times as much methane as the main crop (Lindau & Bollich, 1993; Lindau et al., 1995), likely as a result of the decomposition of rice straw remaining in the field, the additional fertilizer applied, and the high temperature of the early months in which the ratoon crop was grown (Linquist et al., 2018). However, when the emissions are yield-scaled and the decreased labor required for the ratoon crop is considered, the overall GWP is often less than in a conventional crop (Firouzi et al., 2018; Yuan et al., 2019).

The objective of this study is to determine the effect of seeding method, water management, and ratoon cropping on yield and field methane emissions in an Arkansas production rice setting. The methane emissions are measured using the eddy covariance (EC) technique to conduct a full field-scale, paired-field experiment using different seeding, water, and crop treatments on similar rice fields in Lonoke County, Arkansas from 2015 to 2020. This study extends previous work at these sites that focused primarily on the effect of water management on greenhouse gas emissions from 2015 to 2017 (Runkle et al., 2019). Our aims are to (1) further the understanding of the effect of varying degrees of AWD on yield and CH_4 emissions, as the number and duration of drying events differed between fields and seasons, (2) evaluate the impact of water seeding on Arkansas rice, as it is a less common seeding method than dry seeding (Hardke, 2018), and (3) investigate the viability of ratoon rice as a sustainable intensification practice in conjunction with other management strategies. This study is also one of very few to use the eddy covariance technique to evaluate ratoon crop CH_4 flux in rice.

2. Site Description and Methods

2.1 Site Description

This study was conducted on a pair of commercially farmed, adjacent 26 ha rice fields (34°35′ 7.84″ N, 91°45′ 6.02″ W) in Lonoke County, Arkansas during the 2015 through 2020 growing seasons (Figure 1). The fields were predominately (>90%) Perry silty clay, zero-grade leveled, and continuously planted with rice since 2006. The fields were burned to remove previous crop residue each fall and were flooded each winter for two to three months for waterfowl habitat and hunting. The fields were planted with CLXL745 hybrid seed by drill-seeding in 2015, 2016, 2017, and 2018, and water-seeding in 2019 and 2020 (Rice Tec., Alvin, TX). For further information on seeding and management practices for each season, see Table 1. The two fields and instrumentation set-up have been previously described and are registered with Ameriflux as US-HRC and US-HRA for the North and South field, respectively (Runkle, 2021; Reba, 2021; Runkle et al., 2019; Suvočarev et al., 2019).

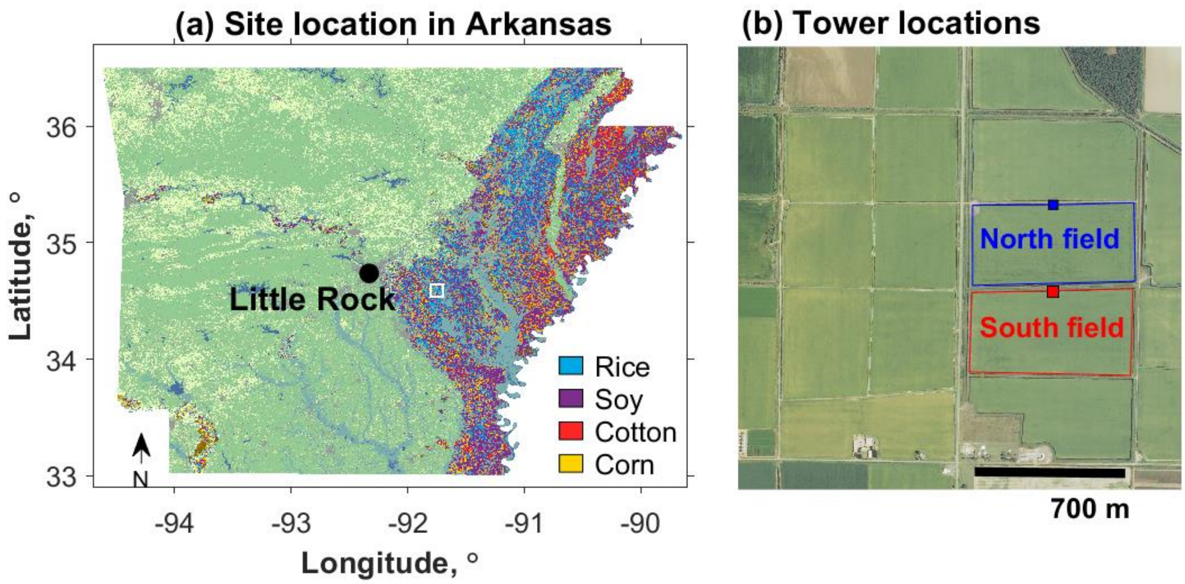

Figure 1: (a) The study site, a pair of fields in Lonoke County, Arkansas, marked by a white square and showing the 2015 CropScape crop cover data set from the National Agricultural Statistics Service (Han et al., 2014) (b) The locations of the eddy covariance (EC) towers are marked on the north side of the fields. The background image is from the USDAFSA- APFO Aerial Photography Field Office within the NAIP and was taken August 22, 2013. Versions of this figure have been previously used (Runkle et al., 2019; Suvočarev et al., 2019).

In 2015, the North and South fields were flooded on May 16 and May 18, respectively, and were managed with a delayed flooding (DF) regime in the North field and an alternate wetting and drying (AWD) regime in the South field. DF is when the rice is dry seeded and allowed to sprout before being continuously flooded for the rest of the season in contrast to AWD, which is when the flooding period is interrupted by shorter drying periods. In 2016, seeding, and therefore flooding and harvest, was delayed due to wet conditions, and both fields were flooded on June 16. Both fields were managed with an AWD regime. In 2017, both fields were flooded on May 18 and managed with a DF regime. In 2018, the North and South fields were flooded on May 6 and May 7, respectively, and both were managed with an AWD regime. In 2019 and 2020, the fields were flooded prior to planting to facilitate water seeding but were managed with an AWD regime throughout the main season. A ratoon crop was grown in both fields in 2020 and was managed with AWD. The 2020 main crop was cut to a height of 40 cm upon harvest and the fields were reflooded within two days of cutting.

Table 1: Planting dates, harvest dates, and field management practices for all years. Abbreviations: MS (main season), RS (ratoon season), DS (dry seeding), WS (water seeding), DF (delayed flooding), and AWD (alternate wetting and drying). Dashes show that the field-season was a ratoon crop and was regrown from a main crop rather than seeded. Drying events were defined as periods where the water table depth fell at least 2 cm below the soil surface for a minimum of 24 hours. Drying events with less than 24 hours of flooded conditions between them were considered to be a single drying period. Only drying events after the initial flooding event and before the final draining event were counted.

Year	**Seeding method**		**Irrigation treatment**		**Days under inundation**		**Number of drying events**		**Start of season**		**End of season**	
Field	**North**	**South**	**North**	**South**	**North**	**South**	**North**	**South**	**North**	**South**	**North**	**South**
2015	DS	DS	DF	AWD	93	57	0	4	8-Apr	7-Apr	19-Aug	19-Aug
2016	DS	DS	AWD	AWD	76	63	2	5	23-Apr	23-Apr	13-Sep	13-Sep
2017	DS	DS	DF	DF	75	84	0	0	10-Apr	9-Apr	27-Aug	27-Aug
2018	DS	DS	AWD	AWD	66	36	3	3	30-Apr	30-Apr	15-Sep	31-Aug
2019	WS	WS	AWD	AWD	42	42	2	4	13-May	13-May	12-Sep	12-Sep
2020 - MS	WS	WS	AWD	AWD	77	90	3	4	2-Apr	2-Apr	19-Aug	18-Aug
2020 - RS	-	-	AWD	AWD	51	49	2	2	20-Aug	19-Aug	8-Nov	9-Nov

2.2 Equipment and Measurements

Figure 2: Eddy covariance and meteorological instrumentation on the study site (South Field) with measuring equipment, taken summer 2021. Photo by Dawson Oakley.

The CH_4 flux, CO_2 flux, latent energy (LE), and sensible heat (H) were measured using the EC technique as part of the Delta-Flux network (Baldocchi et al., 1988; Runkle et al., 2017). Equipment used on the EC towers (Figure 2) included data loggers (CR3000 and CR1000, Campbell Scientific, Inc., Logan UT, USA), temperature and relative humidity sensors (HMP155, Vaisala, Vantaa, Finland), an atmospheric pressure sensor (Barometer 278, Setra, Boxborough, MA, USA), a 2D wind vector sensor (05103−5 propeller wind monitor, R.M. Young, Traverse City, MI, USA) sensors measuring the four components of net radiation (CNR4 radiometer, Kipp & Zonen, Delft, Netherlands), a 3D sonic anemometer (CSAT3, Campbell

Scientific, Inc., Logan, UT, USA), an open path CO_2/H_2O infrared gas analyzer (LI-7500A, LI-COR Inc., Lincoln, NE, USA), and an open-path CH_4 using wavelength modulation spectroscopy (LI-7700, LI-COR Inc., Lincoln, NE, USA). The sonic anemometer wind vector and gas analyzer concentration measurements were recorded at 20 Hz through an Analyzer Interface Unit (LI-7550, LI-COR Inc.) with the LI-COR SMARTflux automated processing system. The equipment was installed at the north end of each field, on tripods 2.2 m (North field; US-HRC) and 2.1 m (South field; US-HRA) above the ground. Precipitation and temperature data for Stuttgart, AR were downloaded from the PRISM database (*PRISM Climate Group*, 2014) and compared to average values from the last 30 years.

Soil temperature was measured at 2 and 4 cm below the soil surface near the towers using thermistors (107, Campbell Scientific, Inc., Logan, UT, USA). Water temperature was also measured using thermistors placed on top of the water and at the soil-water interface. The water table depth was measured with capacitive level transmitters (Nanolevel, Keller America, Newport News, VA, USA). Dissolved O_2 concentrations were measured at the soil-water interface using a dissolved oxygen logger (PME miniDOT, OH, USA). A GPS-enabled John Deere GreenStar 3 2630 Harvest Monitor recorded location-based wet and dry harvest weights from both fields, with measurements approximately 2 m apart (John Deere, IL, USA). Yields were reported on a 13% moisture basis. The equipment setup for this site and study has been previously described (Runkle et al., 2019).

2.3 Data Processing

The raw data from the EC system was processed as half-hourly measurements using EddyPro software (v. 7.0.6, LI-COR Inc., Lincoln, NE). Further processing was done using MATLAB software (v. R2019b, MathWorks Inc., Natick, MA) to remove poor quality data and to gap-fill missing values. Extremely high or low data points were regarded as errors and were removed by establishing upper and lower boundaries for the CH_4 flux and water level datasets. CH_4 flux values higher than 4 μmol m^{-2} s^{-1} or lower than -4 μmol m^{-2} s^{-1} were removed. The absolute value of the difference between consecutive CH_4 flux points was compared and points with differences > 0.4 μmol m^{-2} s^{-1} were removed as well. Water level values above 1 m and below -1 m were removed. Other datapoints were removed when the friction velocity (u*) was ≤ 0.1 m s^{-1}, when the relative signal strength indicator for the CH_4 analyzer was < 10, when the wind direction was between 265° and 95°, when the pitch was >10° or < -10 °, when the along-wind distance providing 90% of the cumulative contribution to the turbulent fluxes was ≥ 400 m, and when the quality flag for the CH_4 analyzer was 2 (on the 0-1-2 flag system accounting for stationarity and turbulence characteristics) for all seasons and fields except for the South field during 2019. In that field and season the EC equipment had technical difficulties that resulted in a limited amount of good quality data (Table 2). For this reason, values with a quality flag of 2 (96.4% of the South field dataset) were retained in the South field dataset for 2019.

Table 2: Percentage of points remaining in the CH_4 flux and water table datasets for each field-season after data processing and before filling large gaps with the neural network model. Abbreviations: MS (main season) and RS (ratoon season).

Year	**Remaining CH_4 flux data (%)**		**Remaining water table data (%)**	
Field	**North**	**South**	**North**	**South**
2015	19.9	23.8	64.6	62.7
2016	26.0	26.2	73.6	72.3
2017	28.1	23.8	95.4	77.0
2018	37.3	45.9	63.8	87.7
2019	6.1	4.6	68.0	77.5
2020 - MS	35.9	31.8	95.0	92.2
2020 - RS	25.2	18.1	100	99.9

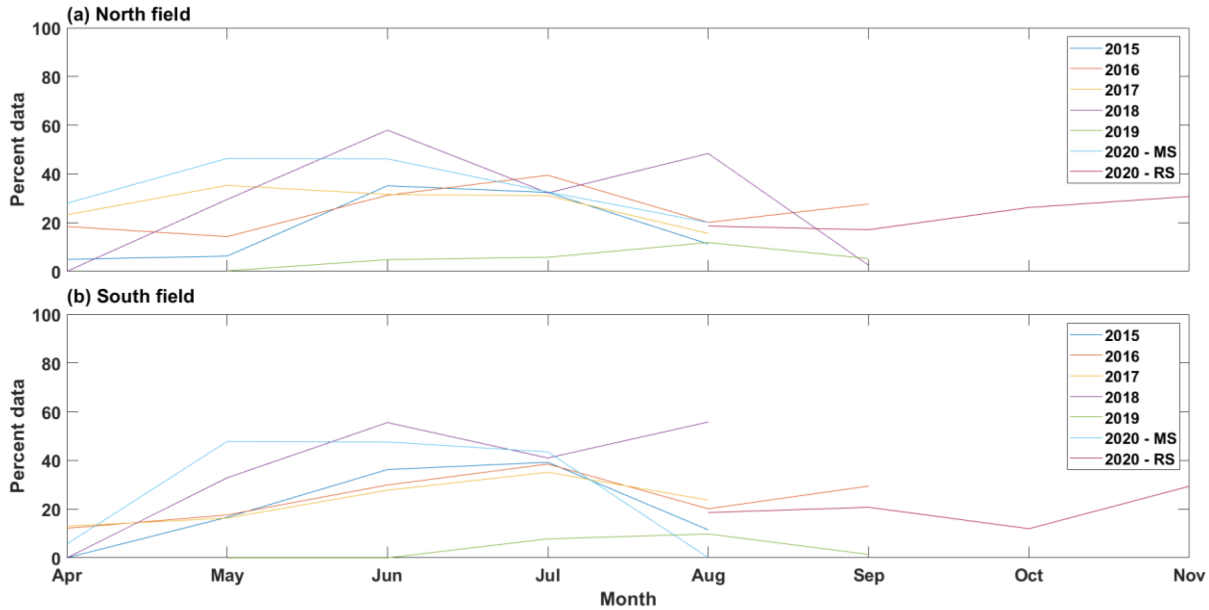

Figure 3: Percentage of data remaining after processing and filling small gaps of less than 6 hours in the CH_4 flux data for each month. Abbreviations: MS (main season) and RS (ratoon season).

Following processing, we needed to be sure there was enough data remaining for accurate gap-filling using the ANN. For this reason, we inspected the percentage of data that remained of the total dataset for both the CH_4 flux and water table data after filling small gaps (Table 2). CH_4 flux data is prone to large gaps due to inadequate turbulence, periods where the wind is blowing in the wrong direction, and technical problems (Irvin et al., 2021). The 2018-2020 CH_4 flux data was evaluated during data processing to determine the major causes of gaps. The 2015-2017 CH_4 flux data was not evaluated because it was acquired pre-processed from a previous study (Runkle et al., 2019). Gaps in 2018-2020 were primarily due to problems with the equipment, with 17.3 to 51.7% of the CH_4 flux dataset being made up of error values and another 4.9 to 16.4 % having poor quality flag values. A further 2.2 to 40.9% of the dataset was removed due to instances where the wind was blowing from the wrong direction or the turbulence in the air was too low.

CH_4 datasets with data coverage as low as 17% have been successfully gap-filled using an ANN (Irvin et al., 2021). For this study, we considered 20% to be a reasonable threshold for predictive purposes. The CH_4 flux data was less well-represented than the water table data, though most of the field-seasons of CH_4 flux data still had at least 20% of their data remaining after processing. Broken down by month, the time periods where the CH_4 flux data was least well-represented were generally at the beginning and end of the season, except for 2019 which had limited data throughout the whole season (Figure 3). Data in 2019 was limited due to problems with the equipment and the firmware and was excluded from further analysis. Since most of each field-season other than those in 2019 had an acceptable number of datapoints, it was decided that the remaining data was sufficient to proceed with gap-filling.

Gaps in the water table data series smaller than 6 hours were filled by linear interpolation. Larger gaps in the 2015 water table data were also filled by interpolation, as the missing points occurred during a period when the field was visibly flooded (Runkle et al., 2019). Larger gaps in the 2016 and 2017 water table data were filled by linear regression with data from a dissolved O_2 sensor (MiniDOT Logger, PME, Vista, CA) at the soil surface and additional water level loggers (Troll 100, In Situ, Fort Collins, CO) in the irrigation ditch at the edges of the field (Runkle et al., 2019). Larger gaps in the 2018-2020 water table data were gap-filled using an artificial neural network (ANN) run for 20 iterations, with the time, soil O_2 sensor data and fuzzy time and season transformation sets as predictor variables (Knox et al., 2014, 2016; Papale & Valentini, 2003). Fuzzy time sets are a method of weighting each measurement based on season and time of day. The time data was broken up into seasonal and daily categories, with the seasonal fuzzy sets divided into winter, spring, summer, and fall, and the daily fuzzy sets divided into morning, afternoon, evening, and night (Papale & Valentini, 2003). Each time point in the fuzzy set was given a value from 0 to 1 based on the proportion of each category it fell into (Papale & Valentini, 2003). For example, a time point in May at 9:00 AM would have values of 0 for winter, 0.667 for spring, 0.333 for summer, 0 for autumn, 1 for morning, 0 for afternoon, 0 for evening, and 0 for night.

Gaps in the CH_4 flux data smaller than 6 hours were filled by linear interpolation. Larger gaps in the CH_4 flux data were gap-filled using the ANN run for 40 iterations. Small gaps made up 1.2 to 23.3% of the missing data, while large gaps made up 76.7 to 97.7% of the missing data. The predictor variables used to gap-fill the CH_4 data were time, the number of days after planting, incoming solar radiation, friction velocity, vapor pressure deficit, air temperature, air pressure, net CO_2 flux, gross carbon uptake, ecosystem respiration, the gap-filled water table data, leaf-area index (LAI), plant height, and the fuzzy time sets. The predictor variable datasets for the CH_4 flux data were not complete and required gap-filling before they could be used. Gaps in the predictor variable datasets smaller than 6 hours were filled by linear interpolation. As the two fields were adjacent, the microclimate data for the two was assumed to be not different, and gaps in the predictor data for one field were filled by data from the other field when available. The remaining gaps were filled with the REddyProcWeb online tool, with the exception of friction velocity which is not supported by the program (Wutzler et al., 2018). The remaining friction velocity gaps were filled by regression with the average wind speed. Once the initial predictor variables were gap-filled, the REddyProc program was used again to partition the net flux into gross carbon uptake and ecosystem respiration (Wutzler et al., 2018).

The CH_4 gap-filling ANN was run for three different models for 2015-2020. In the first model, each field-season was a separate run, with the ratoon season for 2020 run separately from the main season. In the second model, the entire dataset was input as a single run. In the third model, the 2019 data was discarded, and the remaining dataset was input as a single run, using the 2015 season through the 2020 season to predict the 2019 season in its entirety. Based on lower error and greater similarity between runs, it was decided to use the first model for the reported values.

2.4 Data Analysis

We first attempted to use a mixed-effect modelling approach to determine the effect of year, field, irrigation treatment, and seeding method on cumulative CH_4 emissions. MATLAB software (v. R2019b, MathWorks Inc., Natick, MA) was used to create the model. Unfortunately, given the limited amount of data for certain treatments (only 2 usable field-seasons were water seeded and only 3 field-seasons were managed with DF) the model created was not usable. Instead, cumulative emissions from different treatments were grouped and tested for normality using the Shapiro-Wilks test and for equivalence of variance using an F-test.

The cumulative CH_4 emissions were of equal variances but not normally distributed when grouped by irrigation treatment, so a Mann-Whitney U test, a nonparametric equivalent of a t-test, was used to compare emissions between irrigation treatments. The data for each main field-season was also compared by regressing the cumulative CH_4 emissions with different measurements of water treatment to get a clearer picture of the effect of varying degrees of irrigation treatment. Emissions for each field-season were regressed with number of days under inundation, the number of drying events, and the average length of drying and flooding events. Additional tests and regressions were done with adjustments to the cumulative CH_4 flux to account for the possible influence of both year and field effects.

A previous study on the same fields for 2015 through 2017 used the 2017 season as a control to determine the impact of field-to-field differences on cumulative CH_4 emission and we used the same method here (Runkle et al., 2019). The 2017 season was used as a control because in that season, both fields were dry seeded, managed with DF, and planted and harvested within one day of each other. Any differences between the two fields could be attributed to the field effect. The season-long South to North field CH_4 emissions ratio was 0.67, which was used to adjust the North field data (Runkle et al., 2019). The cumulative growing degree days were used to adjust the cumulative CH_4 emissions for possible year effect. Since the primary difference between years that can be accounted for with the data available is the climate, we divided the cumulative CH_4 emissions for each field-season by the cumulative growing degree days for each year.

CH_4 flux rates vary throughout the season, so the temporal aspect of emissions was investigated by breaking the flux data for each field-season into three temporal stages based on weekly developmental data from the 2019 season and the growth stages of Arkansas rice (Hardke, 2018). These stages were the vegetative stage, the reproductive stage, and the maturation stage. The vegetative stage was defined as the period from 0-66 days after planting and ended at panicle differentiation. The reproductive stage was defined as the period from 67-85 days after planting and ended at flowering. The maturation stage was defined as the period from 86 days after planting to the date of harvest.

Yields in both irrigation treatments were normally distributed and had equal variances with each other, so a t-test was used to find the effect of irrigation treatment on the yield. Yield between years was insufficient to apply statistical analysis with any confidence, as there were only two fields per year. Yield between seeding methods was not normally distributed so a Mann-Whitney U test was performed to find the effect of seeding method on yield. Yield between fields was normally distributed and had equal variances, so a t-test was used to find the effect of field effect on yield.

To determine whether the ratoon crop was cost-effective in this study, we performed an exploratory analysis of the cost of its production. The cost and net return of the ratoon crop was estimated using a rice crop enterprise budget (University of Arkansas Division of Agriculture Research & Extension, 2022), which considered the costs of the amount and method of application of pesticide, herbicide, and fertilizer, the fuel required for operating machinery and pumping water, hourly labor, and equipment maintenance, as well as the expected return based on average price per yield.

2.5 Literature Synthesis

A literature review and synthesis of peer-reviewed articles on the yield of rice ratoon cropping was performed through the University of Arkansas library database. The literature search spanned 1993 through 2021 encompassing 11 studies, 199 sites, and 2 countries. Only articles that included both the main and ratoon crop yield were included in the synthesis. Sites where the ratoon yield exceeded the main yield were excluded, as the main yield for these sites was poor. Poor main yield is indicative of lodging or other crop damage, and the purpose of this review was to gain a clearer picture of ratoon yield under good conditions. Data on fertilizer treatment and cultivar was also recorded when available.

3. Results

3.1 Climate

The PRISM dataset revealed that all seasons had greater annual precipitation than the 30-year average (1288 mm) with a range of 1411 to 1925 mm. The main growing season precipitation, defined as the precipitation from April through September, was greater than the 30-year average of 598 mm for all years except 2015, which had 390 mm (Table 3) The 2020 ratoon season precipitation, defined as precipitation from August through November, was 506 mm, greater than the 30-year average of 381 mm (Table 3).

Table 3: Monthly and annual precipitation for each year of the study and the 30-year average. Data taken from the PRISM database (*PRISM Climate Group*, 2014) for Stuttgart, AR.

Precipitation (mm)							
Month	**PRISM 30-year average**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
Jan	98	74	61	90	83	118	192
Feb	104	83	76	77	322	207	193
Mar	129	220	322	81	214	121	180
Apr	142	121	193	257	196	288	161
May	126	198	98	159	76	212	148
Jun	84	70	49	128	71	154	124
Jul	86	78	89	190	77	187	65
Aug	78	38	198	103	149	148	166
Sept	81	6	15	40	224	28	139
Oct	109	87	47	31	158	214	148
Nov	112	270	79	34	155	106	53
Dec	138	166	197	244	202	62	158
Yearly total	1288	1411	1423	1433	1925	1844	1726

The monthly average minimum, maximum, and mean temperatures for the study years were not that different (within 1 °C) to the 30-year average except for 2016 which had an average annual minimum temperature 1.2 °C higher than the 30-year average. Compared to the monthly mean temperatures for the 30-year average, the average monthly mean temperature during the main growing season was warmer for April and July of 2015, June, July, and September of 2016, April of 2017, May and June of 2018 May and September of 2019 (Table 4). Warmer temperatures ranged from 1.1 to 3.9 °C above the 30-year average. The average monthly mean temperature was cooler than the 30-year average for August of 2017, and April, October, and November of 2020 (Table 4). Cooler temperatures ranged from 1.3 to 1.9 °C below the 30-year average.

Table 4: Monthly and annual average temperature for each year of the study and the 30-year average. Data taken from the PRISM database (*PRISM Climate Group*, 2014) for Stuttgart, AR.

Mean Temperature (ºC)							
Month	**PRISM 30-year average**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
Jan	5.0	3.9	4.4	7.8	2.1	5.9	7.1
Feb	7.3	2.4	8.6	11.6	8.1	8.5	7.4
Mar	11.7	10.2	13.7	13.9	13.2	10.0	13.8
Apr	16.9	18.1	17.7	18.8	13.7	16.9	15.5
May	21.9	22.2	21.0	21.4	25.2	23.1	21.0
Jun	26.2	26.9	27.3	25.2	28.0	25.8	25.9
Jul	27.7	28.8	28.8	27.8	28.3	27.4	28.3
Aug	27.1	26.5	27.3	25.7	26.5	27.4	26.2
Sept	23.5	24.5	25.4	23.5	24.4	27.4	22.8
Oct	17.4	18.2	20.3	18.3	18.3	17.4	16.1
Nov	11.1	13.1	13.6	12.4	8.8	8.2	13.0
Dec	6.6	11.1	6.7	6.4	7.5	8.3	6.5
Yearly average	16.9	17.2	17.9	17.7	17.0	17.2	17.0

3.2 Yield

For the main seasons, the yield appeared to vary little by year or season, with most yields in the range of 9 to 11 t ha^{-1} (Table 5, Figure 4). Both fields from the 2016 season had greater yields (11.0 t ha^{-1}) than the other field-seasons. The North field in 2018 suffered crop damage due to weeds and had the lowest yield of all the field-seasons (7.1 t ha^{-1}). Yield did not vary significantly by irrigation treatment ($p > 0.05$ using the t-test), seeding method ($p > 0.05$ using the Mann-Whitney U test), or field ($p > 0.05$ using the t-test) (Figure 4). The ratoon yield for 2020 was 11.9% that of the main yield for the North field and 13.9% that of the main yield for the South field.

Table 5: Yield for the North and South fields during each season in ton ha^{-1}; Yield is at 13% moisture content. Abbreviations: MS (main season) and RS (ratoon season).

Year	North field yield (t ha^{-1})	South field yield (t ha^{-1})
2015	9.3	9.7
2016	11.0	11.0
2017	9.8	10.6
2018	7.1	9.3
2019	9.1	8.6
2020 – MS	10.9	10.8
2020 – RS	1.3	1.5

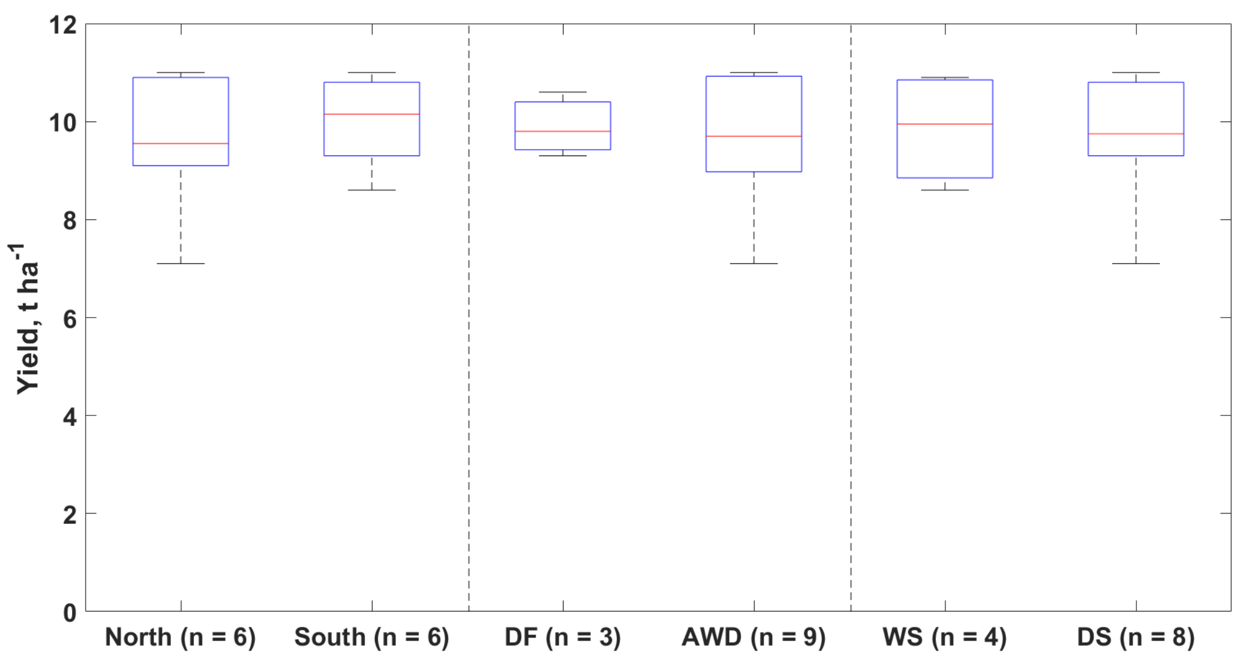

Figure 4: Plot of yield ranges for different fields and treatments. Abbreviations: MS (main season), RS (ratoon season), DS (dry seeding), WS (water seeding), DF (delayed flooding), and AWD (alternate wetting and drying). Note that on these boxplots, the box represents the interquartile range, the red line represents the median, and the whiskers represent the minimum and maximum, excluding outliers (points more than 1.5 times the interquartile range about the 75th percentile or below the 25th percentile).

Compared to the main crop, the financial input for the ratoon crop was minimal. Herbicide was applied aerially to the main crop 7 times, but only once to the ratoon crop. Similarly, 112 kg ha^{-1} of DAP and 532 kg ha^{-1} of urea were applied to the main crop, while only

168 kg ha^{-1} was applied to the ratoon crop. The ratoon crop required much less fuel for the use of heavy equipment than the main crop because the field was plowed before the main crop but was not plowed before the ratoon crop. Entering the farm inputs for the ratoon season into the crop enterprise budget resulted in a net profit of \$66.28 ha^{-1} for the South field and \$5.74 ha^{-1} for the North field, making it cost-effective. The South field had a higher profit than the North field because the breakeven point, the yield at which financial input was the same as the amount received from the sale of the rice, was 1.28 t ha^{-1}, which was only slightly lower than the North field yield of 1.3 t ha^{-1}. The average profit for an Arkansas rice field in 2021 was \$496.85 ha^{-1} (University of Arkansas Division of Agriculture Research & Extension, 2021), so the ratoon crop returned a lower profit than the main crop.

3.3 CH_4 Flux Dynamics

Most of the field-seasons followed a similar general pattern of low CH_4 flux early in the season, a gradual increase reaching a maximum in mid-to-late summer, and a decrease until the final draining period followed by a large spike (Figures 5-7). Spikes were characterized by a sudden sharp increase in CH_4 flux followed by an equally sharp decrease. Spikes had a short duration, generally less than 3 days and were determined by visual inspection of the CH_4 flux graphs. An exception to this pattern of gradually increasing emissions followed by a decline was the North field during 2015 (Figure 5a), which had a second period of increasing flux and a second peak before the final draining period. Additionally, the South field in 2015 (Figure 5a), the South field in 2018 (Figure 6c), and the North field in 2020 (Figure 7a), all lacked the end of season emissions spike. For all years except 2020, the North field had greater baseline flux levels than the South field for most of the season, regardless of irrigation or seeding treatment.

Figure 5: (a) Interpolated, gap-filled daily CH_4 flux for 2015. (b) Water level measurements for 2015. (c) Interpolated, gap-filled daily CH_4 flux for 2016. (c) Water level measurements for 2016. The North field in 2015 was managed with DF while the South field in 2015 and both fields in 2016 were managed with AWD. All fields were dry seeded. Note the difference in scale between the y axes in (a) and (c). Darker points indicate observed data while paler lines indicate modelled data.

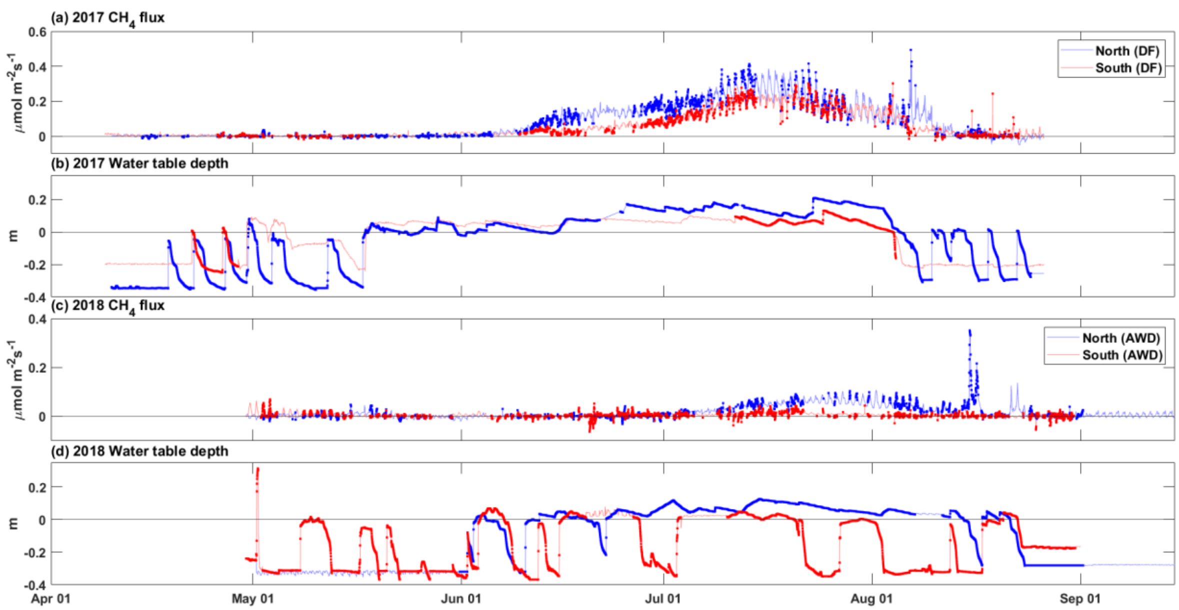

Figure 6: (a) Interpolated, gap-filled daily CH_4 flux for 2017. (b) Water level measurements for 2017. (c) Interpolated, gap-filled daily CH_4 flux for 2018. (c) Water level measurements for 2018. Both fields in 2017 were managed with DF while both fields in 2018 were managed with AWD. All fields were dry seeded. Note the difference in scale between the y-axis in (a) and the y-axis in (c). Darker points indicate observed data while paler lines indicate modelled data.

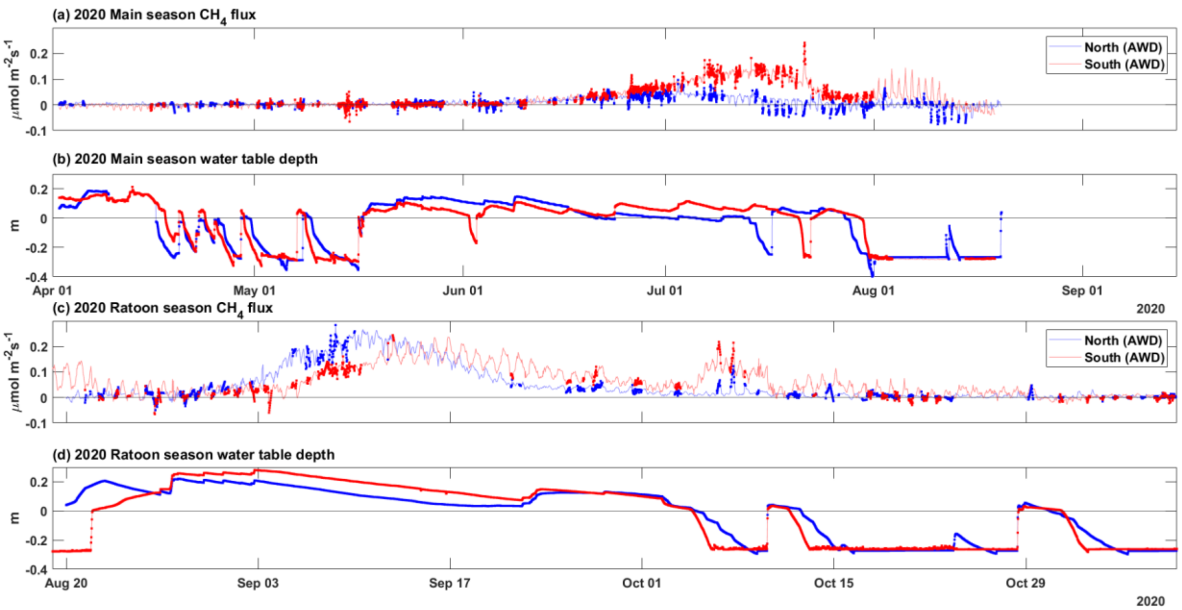

Figure 7: (a) Interpolated, gap-filled daily CH_4 flux for the 2020 main season. (b) Water level measurements for the 2020 main season. (c) Interpolated, gap-filled daily CH_4 flux for the 2020 ratoon season. (c) Water level measurements for the 2020 ratoon season. The main season fields were managed with AWD while the ratoon fields were continuously flooded. The main season fields were water seeded. Darker points indicate observed data while paler lines indicate modelled data.

The CH_4 flux was related to the water level in the field as it tended to increase during flooded periods and at the beginning of drying events. Periods where the level of CH_4 emissions slowly increased corresponded to prolonged flooded periods, while most CH_4 spikes corresponded to the beginning of a drying event, as in mid-July for the South field in 2015. The drying events that corresponded to a spike in emissions occurred after longer flooded periods, and so were primarily during the latter half of the season. Early season drying events were not associated with CH_4 spikes. For field-seasons with multiple spikes, the level of emissions after each spike was always lower than the level before it, suggesting that the drying periods did lower the flux rates, despite the initial increase. The field-seasons that did not have CH_4 spikes after the final draining event had drying events within the last month of the season, suggesting that the flux rate had not increased enough following the previous drying event to result in a spike.

Spikes not associated with a drying event have other potential explanations. The spikes during July and August in the North field in 2015 (Figure 5a) are associated with instances where the water table level dipped below the soil surface briefly, suggesting that even without a complete drying event the water level was low enough to release the CH_4 trapped in the soil. The spikes during August in the South field in 2017 (Figure 6a) occur following the final drain and may be caused by remaining pockets of trapped CH_4 being released as the soil dries further. For all years, spikes from field-seasons treated with a DF regime (ranging from 0.1 to 1.1 µmol m^{-2} s^{-1}) rather than an AWD regime (ranging from 0.1 to 0.6 µmol m^{-2} s^{-1}) were larger.

The CH_4 emissions increased more quickly during the early part of the 2020 ratoon season than the 2020 main season, reaching the same level as the maximum steady flux rate of the main season within three weeks, an increase that took more than a month for the main season (Figure 7a, Figure 7c). The field patterns for the ratoon season were also different from the main season as the South field, which had higher emissions throughout most of the main season, was overtaken by the North field during mid-September of the ratoon season. Note that there is a disconnect between the low South field CH_4 emissions at the end of the 2020 main season and the higher South field CH_4 emissions at the beginning of the 2020 ratoon season. This disconnect is because the gap-filling model was run separately for the ratoon and main season and the South field lacked observed CH_4 data for that period. The percent of available data for the South field during the ratoon season was only 18.1%, as opposed to the 31.8% available during the main season.

The ratoon season responded to the irrigation treatment similarly to the main seasons, with spikes in both fields following the first drying event on October 4 though only the South field had a spike following the second drying event on October 11, possibly because the two drying events were close together, with only 1.6 days of flooding between events (Figure 7b, Figure 7d). Neither field had a spike following the final drain event on October 30, which was 9 days before the ratoon harvest.

3.4 Cumulative CH_4 Emissions

Table 6: Management practices, methane emissions, and yield-scaled methane emissions for each field-season. Abbreviations: MS (main season), RS (ratoon season), DS (dry seeding), WS (water seeding), DF (delayed flooding), and AWD (alternate wetting and drying). Uncertainty ranges were calculated from the 95% confidence interval of cumulative flux variations from the 40 gap-filling runs, as in (Runkle et al., 2019), where errors due to gap-filling were significantly greater than the relative uncertainty of measured flux values.

Year	**Seeding method**		**Irrigation treatment**		**CH_4 flux, kg CH_4-C ha^{-1}**		**Yield-normalized flux, kg CH_4-C ton^{-1}**	
Field	**North**	**South**	**North**	**South**	**North**	**South**	**North**	**South**
2015	DS	DS	DF	AWD	132.5 ± 3.5	35.3 ± 5.6	14.2	3.6
2016	DS	DS	AWD	AWD	29.0 ± 1.1	7.1 ± 0.6	2.6	0.6
2017	DS	DS	DF	DF	114.5 ± 1.5	77.2 ± 2.2	11.7	7.3
2018	DS	DS	AWD	AWD	26.6 ± 1.5	5.8 ± 0.3	3.7	0.6
2020 - MS	WS	WS	AWD	AWD	11.0 ± 0.5	40.7 ± 1.5	1.0	3.8
2020 - RS	-	-	AWD	AWD	39.7 ± 1.0	50.7 ± 2.4	30.5	33.8

For all seasons except 2020, cumulative CH_4 emissions were greater from the North field than the South field (Table 6). In 2020 the water level in the North field was maintained at a level within 1 cm of the soil surface for the majority of July, and it is possible that this lower water table depth relative to flooded periods from other field-seasons prevented soil conditions from becoming completely anoxic and lowered the amount of CH_4 produced. Fields managed with DF produced greater emissions in general (Figure 8), with the highest emissions from the North field in 2015, which was dry seeded and had the highest number of days under inundation. Fields managed with AWD produced lower emissions, though the magnitude varied depending on the duration and frequency of the drying periods. The South field in 2018 produced the least emissions and had the least number of days under inundation. The range of emissions from the DF treatments was 77.2 to 132.5 kg CH_4 ha^{-1} and the range of emissions from the main season AWD treatments was 5.8 to 40.7 kg CH_4 kg CH_4 ha^{-1}.

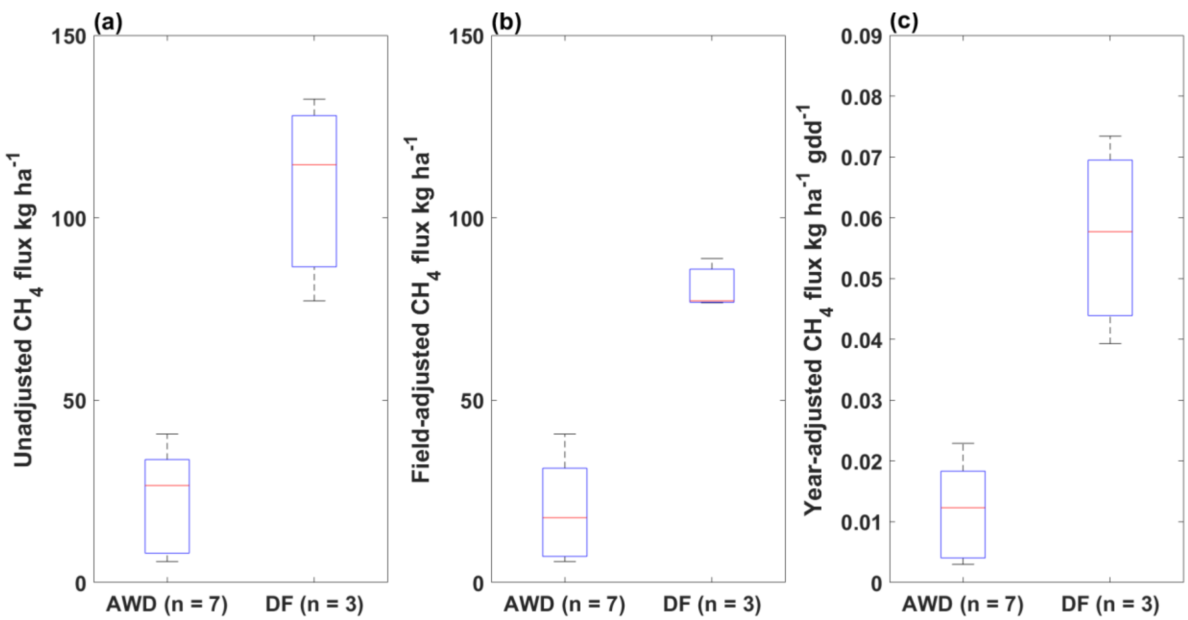

Figure 8: Plot of the ranges of (a) unadjusted cumulative CH_4 flux, (b) field-adjusted cumulative CH_4 flux, and (c) yield-adjusted cumulative CH_4 flux under different irrigation treatments. Abbreviations: DF (delayed flooding), and AWD (alternate wetting and drying).

The irrigation treatment had significant ($p < 0.05$) impact on the field-adjusted cumulative CH_4 emissions, with emissions from field-seasons managed with AWD being 79.4% less than DF emissions on average for unadjusted CH_4 emissions, 76.4% less for field-adjusted CH_4 emissions, and 79.6% less for year-adjusted emissions (Figure 8). For 2015, which had paired AWD and DF irrigation treatments, the cumulative emissions from the field managed with AWD were 73.4% less on average than emissions from the DF field prior to any adjustment, and 60.2% less when adjusted for field effect.

Seasons where the fields were managed with the same seeding method and irrigation treatment still showed variation. The South field produced 75.5% and 78.2% less unadjusted CH_4 than the North field in 2016 and 2018 respectively, when both seasons were dry seeded and managed with AWD. When adjusted for field effect, the South field produced 63.6% and 67.4% less CH_4 than the North field in 2016 and 2018, respectively (Figure 9). The reverse was true in 2020, with the North field producing 73.0% less CH_4 than the South field when unadjusted and 81.8% less when adjusted for field effect, though both fields were water seeded and managed with AWD (Figure 9). In 2016, the South field had 3 more drying events than the North field, and in 2018, the South field had longer drying events than the North field, with an average length of drying event of 15 days for the South field and 5 days for the North field. In 2020 the North field water table depth was near or below the soil surface for approximately 26 days from mid-June to mid-July. The water level did not drop low enough to be considered a drying event but may have been sufficiently low to interrupt methanogenesis.

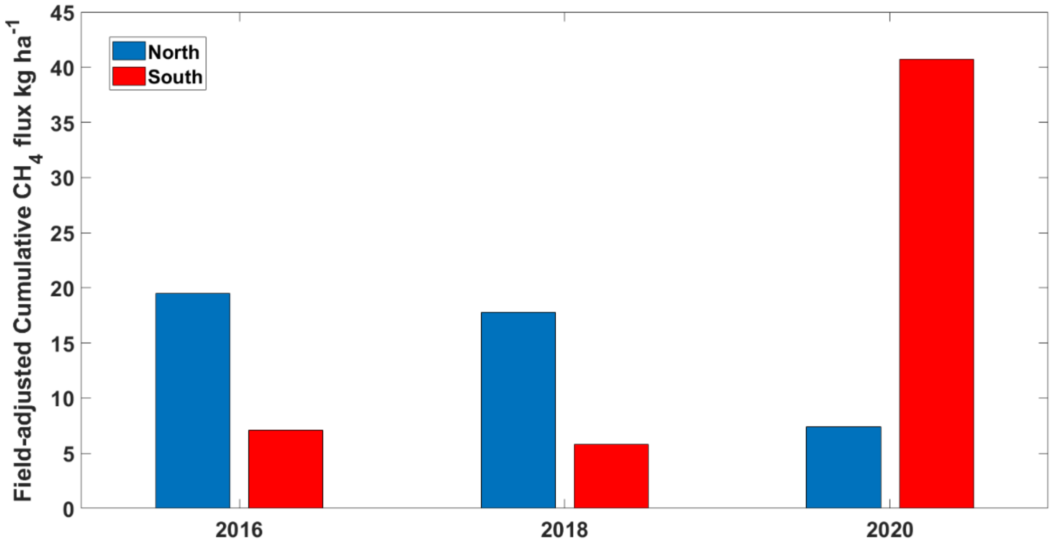

Figure 9: Plot of field-adjusted cumulative CH_4 flux ranges for all seasons where both fields were managed with the same seeding method (dry-seeding in 2016 and 2018; water-seeding in 2020) and irrigation treatment (AWD).

We found that there was no significant relationship ($r^2 = 0.4$, $p = 0.07$ using the F-test) between the unadjusted cumulative CH_4 flux from the main season and the number of days under inundation, but a significant relationship ($r^2 = 0.7$, $p = 0.003$ using the F-test) between the unadjusted cumulative emissions and the number of drying events, where the cumulative emissions decreased as the number of drying events increased (Figure 10 a,b). When the cumulative CH_4 flux was adjusted for field effect, the correlation between cumulative emissions and days under inundation became significant ($r^2 = 0.4$, $p = 0.05$ using the F-test), while the relationship between cumulative emissions and the number of drying events remained much the same ($r_2 = 0.7$, $p = 0.004$ using the F-test) (Figure 10 b,d). Adjusting for yearly effect using growing degree days did not result in a stronger relationship for either trend ($r^2 = 0.4$, $p = 0.06$ for the relationship between cumulative CH_4 and the number of days under inundation, $r^2 = 0.4$ and $p = 0.004$ for the relationship between cumulative CH_4 and the number of drying events;

data not shown). Additional regressions were done with the datapoints divided into two groups based on irrigation treatment and neither of them were significant ($p > 0.05$ using the F-test, data not shown).

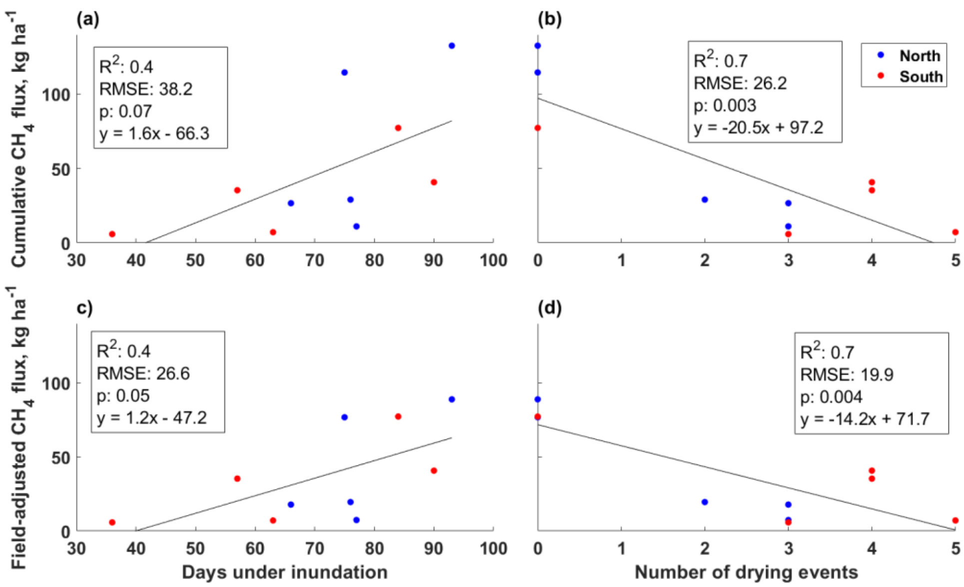

Figure 10: Cumulative CH_4 flux for the main seasons plotted against a) the number of days under inundation and b) the number of drying events; Field-adjusted cumulative CH_4 flux for the main seasons plotted against c) the number of days under inundation and d) the number of drying events. Drying events were defined as periods after the initial flood and before the final draining event where the water level dropped at least 2 cm below the surface for a minimum of 24 hours.

The average length of the drying events ranged from 0 to 14.7 days, with the field-seasons managed with AWD having drying events ranging from 4.5 to 14.7 days in length. The drying event length was approximately 4 to 6 days for most field-seasons with about 2 to 3 days standard deviation, but the North field in 2016 and the South field in 2018 both had long drying events that raised the average. The North field in 2016 had an event that lasted 16.1 days during late May and early June, and the South field in 2018 had an event that lasted 30.0 days during late July and mid-August. The average length of the flooding events ranged from 8.5 to 88.4

days, with the field-seasons managed DF having flooding events ranging from 71.2 to 88.4 days in length while the field-seasons managed with AWD ranged from 8.5 to 22.8 days. The length of the flooding events varied more than the length of the drying events, though the North field in 2016 had the longest flooding event which lasted 54.7 days during June through August. The shortest flooding events occurred in April of 2020, with both fields having events of less than a day.

The cumulative CH_4 emissions were significantly correlated with the length of the drying events and flooding events. When the average length of the drying events for each field-season was regressed with the adjusted and unadjusted cumulative CH_4 emissions, all the trends were significant, but the field-adjusted cumulative CH_4 had the strongest relationship ($r^2 = 0.7$, $p = 0.005$ using the F-test). The relationship between the unadjusted emissions and the drying event length ($r^2 = 0.6$, $p = 0.009$ using the F-test) and the year-adjusted emissions and the drying event length ($r^2 = 0.6$, $p = 0.01$ using the F-test) were nearly the same (Figure 11). The cumulative CH_4 emissions had a stronger relationship with the average length of the flooding events than the average length of the drying events, with all regressions having an $r^2 = 0.9$ (Figure 12). The relationship between the length of the flooding events and the unadjusted CH_4 emissions had a better significance level ($p = 0.00007$) than the field-adjusted CH_4 emissions ($p = 0.00009$) and the year-adjusted CH_4 emissions ($p = 0.0001$), though these differences were very slight. When the dataset was divided into two groups based on irrigation treatment and each was regressed separately, there was no correlation between the length of drying or flooding events and cumulative CH_4 emissions for either treatment ($p > 0.05$ using the F-test, data not shown).

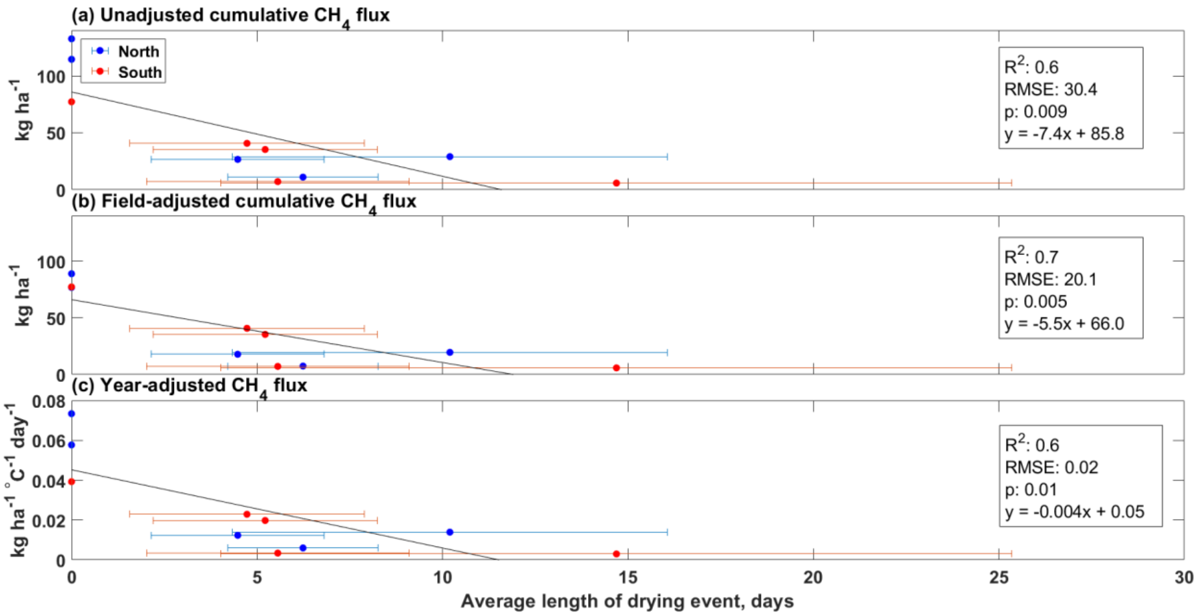

Figure 11: Cumulative CH_4 flux for the main seasons (a) unadjusted, (b) field-adjusted, and (c) year-adjusted, plotted against the average length of drying events for each field-season. Error bars represent the standard deviation of event lengths. Note that the number of drying events per season is different in each field-season, so the standard deviation covers different population sizes.

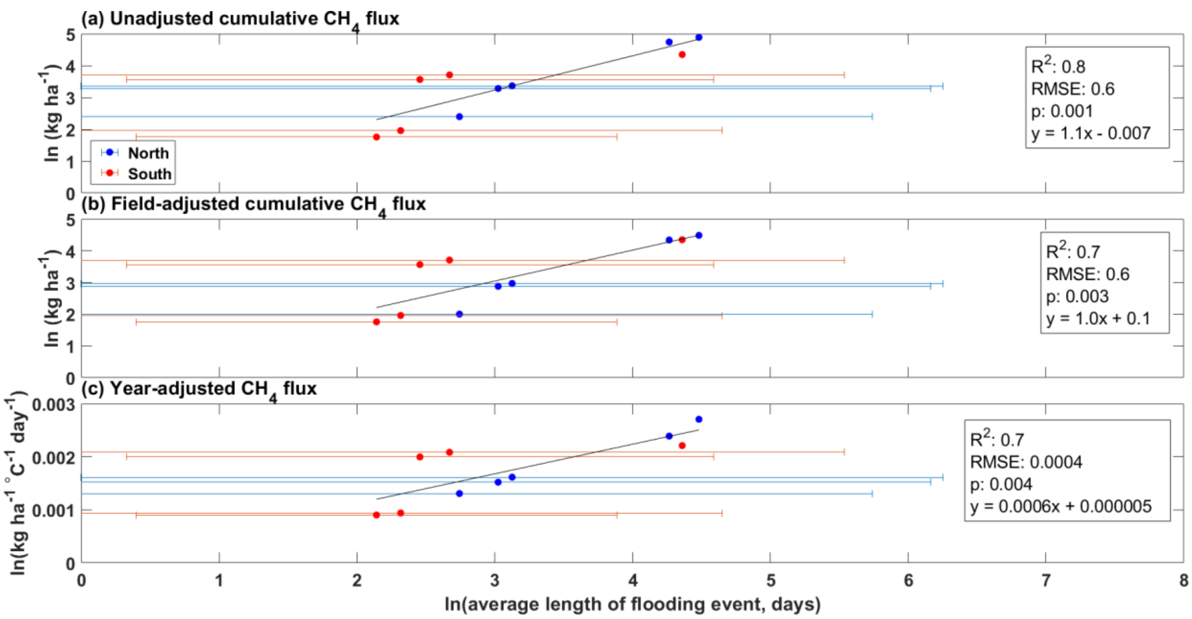

Figure 12: Cumulative CH_4 flux for the main seasons (a) unadjusted, (b) field-adjusted, and (c) year-adjusted, plotted against the average length of flooding events for each field-season. Error bars come from the standard deviation. Both axes in all three subplots were normalized by natural log-scaling. Note that the number of flooding events per season is different in each field-season, so the standard deviation covers different population sizes.

To determine the effects of time of season on emissions, each season was divided into vegetative, reproductive, and maturation growth stages and the CH_4 emissions were summed for each stage (Table 7). Emissions were similar during the vegetative and reproductive stages and were highest during the maturation stage (Figure 13). The North field in 2015 was an outlier in both the vegetative and reproductive stages, with the highest CH_4 emissions of both stages (Figure 13). The North field in 2017 was also an outlier in the reproductive stage, with the second-highest emissions for that stage (Figure 13). Both outlier field-seasons were dry seeded and managed with DF. Emissions during 2020, the only water seeded year, were on the low end of the range of emissions for the vegetative stage. The South field in 2020 even acted as a CH_4 sink during the vegetative stage, which can happen when the methanotrophic bacteria in the soil are more active than the methanogenic bacteria (Banker et al., 1995). However, neither 2020 field was an outlier, and the emissions from both dry seeded 2016 fields were similar to emissions from the North field in 2020.

Table 7: Cumulative methane emissions for each main field-season broken into vegetative, reproductive, and maturation growth stages. Uncertainty ranges were calculated from the 95% confidence interval of cumulative flux variations from the 40 runs, as in (Runkle et al., 2019).

Year	**Vegetative stage CH_4 flux, kg CH_4-C ha^{-1}**		**Reproductive stage CH_4 flux, kg CH_4-C ha^{-1}**		**Maturation stage CH_4 flux, kg CH_4-C ha^{-1}**	
Field	**North**	**South**	**North**	**South**	**North**	**South**
2015	19.6 ± 2.0	13.9 ± 5.3	44.0 ± 0.3	3.9 ± 0.3	70.6 ± 2.2	17.6 ± 1.8
2016	2.0 ± 0.7	1.3 ± 5.3	1.9 ± 0.1	1.6 ± 0.1	25.1 ± 0.8	4.1 ± 0.3
2017	6.8 ± 0.4	4.3 ± 1.5	28.9 ± 0.3	11.2 ± 0.2	78.6 ± 1.2	61.5 ± 1.0
2018	2.2 ± 0.4	2.4 ± 0.2	9.1 ± 0.1	2.4 ± 0.05	15.9 ± 1.2	1.2 ± 0.07
2020	1.9 ± 0.3	-0.5 ± 0.7	4.3 ± 0.1	5.4 ± 0.1	5.6 ± 0.4	35.3 ± 1.2

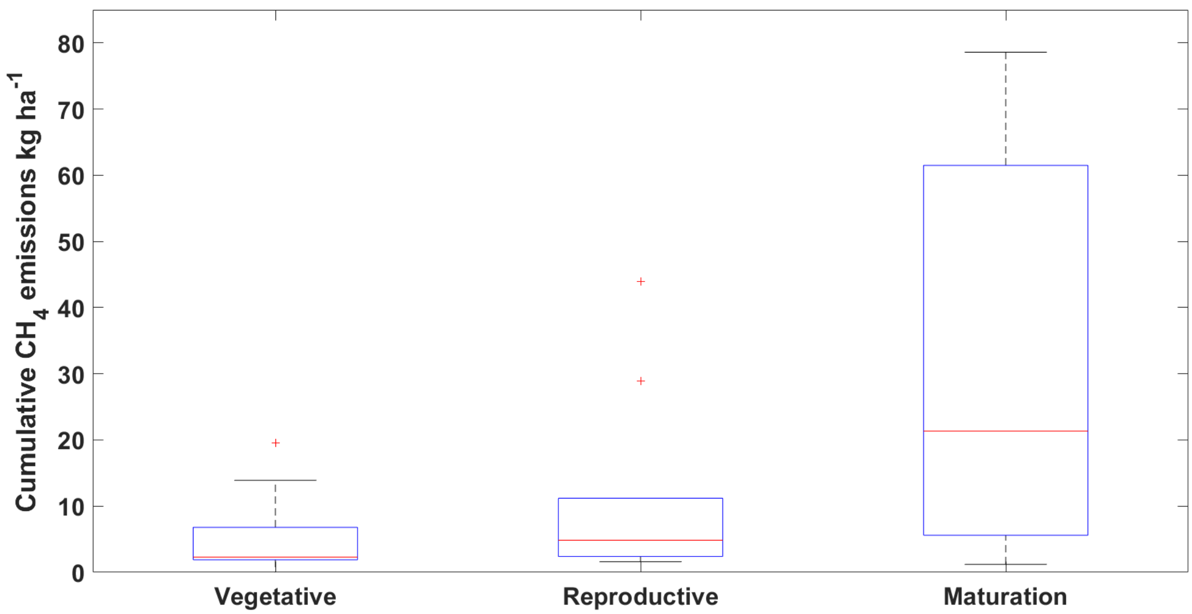

Figure 13: Cumulative CH_4 flux for the main seasons during each growth stage.

CH_4 emissions from the 2020 ratoon season were compared to the 2020 main season rather than fallow season emissions from other years because fallow season emissions tend to be much lower than growing season emissions (Reba et al., 2019). Fallow season emissions are highest during winter flooding (Reba et al., 2019), but winter flooding for the other years did not start until November which is when the ratoon season ended. We assumed CH_4 emissions during the equivalent fallow period (mid-August to early November) were negligible in most other years due to the lack of sustained flooding and the reduced level of biomass on the field due to the burning of the residual litter following harvest.

The North and South fields during the 2020 ratoon season emitted 2.6 and 3.6 times the cumulative CH_4 of the North field during the 2020 main season, respectively. The North field during the 2020 ratoon season produced emissions 2.5% lower than that of the South field main season while the South field during the 2020 ratoon season produced emissions 24.6% higher than the South field main season. On a yield-scaled basis, the ratoon seasons produced 8.0 to 33.8 times the CH_4 flux per ton of rice yield than the main seasons.

4. Discussion

This study considered the effect of multiple management practices on rice yield and CH_4 emissions in Arkansas. The effects of these treatments were not entirely separable from the effects of season and field, although interference was minimized as much as possible by selecting specific fields and time periods for comparison and adjusting data for field effect and irrigation treatment effect when necessary.

Some differences in cumulative CH_4 emissions cannot be attributed to irrigation management or seeding treatment. The paired fields were adjacent, zero-grade-levelled, and grown under the same climate conditions during each season, but in all seasons except 2020 the North field emitted more cumulative CH_4 than the South field, even when seeding and irrigation treatments were the same for both fields. This may be partly due to differences in soil composition between fields. Both fields had soil that was at least 90% Perry silty clay, but additional soil texture analysis reported in Runkle et al 2019 showed significantly higher clay content in North field than South field (60 vs 41% at 0-10 cm depth). Soils with a lower clay content are generally assumed to have greater potential for methane emissions, as clay soils tend to trap CH_4 below the surface (Le Mer & Roger, 2001), but the North field, which had the higher clay content, emitted more CH_4 than the South field. It is possible that during short drying events, the field with higher clay content retained more moisture than the field with lower clay content, leading to lower reductions in CH_4. Other differences in soil composition between fields may also exist, such as different soil microbiomes or levels of soil organic matter. Soil with higher organic matter content has higher potential for methanogenesis (Runkle et al., 2019) and changes in the soil microbiome can decrease of increase the amount of CH_4 produced depending on whether the community has a low or high number of methanogens (Le Mer & Roger, 2001).

Climate and living plant biomass interacted to produce the general pattern of increasing CH_4 flux during the mid to late summer that was seen across the main seasons. The highest steady CH_4 flux rates occurred in July and August, which were the months with the highest mean temperatures, as well as the months where the rice plants had reached maximum vegetative growth and moved into the reproductive and maturation stages (Hardke et al., 2020). When broken down by growth stage, emissions generally increased with each successive stage, reaching a maximum during the maturation stage. The only exception was the South field in 2015, which had greater emissions during the vegetative stage than during the reproductive stage, possibly because it had a 15-day flooding period near the end of the vegetative stage. Methanogenesis is enhanced under high temperatures and CH_4 transport from the soil to the atmosphere is most often mediated by the aerenchyma of the rice plants (Le Mer & Roger, 2001). The combination of favorable conditions for methanogenesis and high rates of plant transport likely led to high rates of CH_4 flux during the late summer at the Arkansas rice fields.

Previous studies have found that water seeded rice produced higher CH_4 emissions than dry seeded rice, attributing the increase to longer periods of anaerobic conditions during the early growth period than dry seeded rice (Hang et al., 2014; Ko & Kang, 2000; Tao et al., 2016). The seeding method was one of the more difficult treatments to differentiate in this study because of the limited number (4) of water seeding treatments, of which only 2 provided usable data. Since any effect from the seeding method would likely be seen in the early part of the season, we compared cumulative CH_4 emissions from the vegetative stage. Emissions for both water seeded fields fell within 1.5 times the interquartile range of all vegetative season emissions and we concluded that seeding method had no attributable effect on emissions here.

Irrigation practices had a significant effect on CH_4 flux in this study, with AWD reducing emissions by 73.4% with respect to the DF treatment; see also (Runkle et al., 2019) for results from 2015-2017. Both studies had emissions reductions within the range of other AWD studies performed on United States rice fields, between 39 and 83% (Linquist et al., 2018; Runkle et al., 2019). The level of emission reduction was not the same for all AWD field-seasons. Even when the field-effect factor was applied, cumulative CH_4 emissions from fields under the same treatments differed (Figure 9). This difference does not indicate that the adjustment for field-effect was insufficient, but that AWD management was not the same between fields. There were variations in the length and duration of drying events between fields and reducing the time the field is inundated can reduce CH_4 emissions (Balaine et al., 2019; Linquist et al., 2015).

When we regressed cumulative CH_4 emissions with the number of days under inundation and the number of drying events, we found that there was a significant decrease in the amount of CH_4 emitted as the number of drying events increased and a significant increase in the amount of field-adjusted CH_4 emitted when the number of days under inundation increased. That cumulative CH_4 emissions increased with the number of days under inundation and decreased with the number of drying events supports earlier studies that found that the reduction in CH_4 emissions due to AWD irrigation was greater when the drying periods were longer (Balaine et al., 2019; Linquist et al., 2015).

When considering the regression relationships, however, it is important to note that when the field-seasons were separated by irrigation treatment none of the relationships were significant. For the regressions between the number of drying events, the length of drying and flooding events, and cumulative CH_4 emissions, there are clearly two groups of data, with field-seasons managed with AWD and DF in different clusters (Figure 10 b, Figure 10 d, Figure 11, Figure 12). It is possible that we found only a difference in emissions by irrigation treatment and not an actual trend. Likewise, there may be separate trends for AWD and DF that we can't distinguish because of our limited number of field-seasons.

The duration of drying and flooding events was significantly correlated with the cumulative CH_4 emissions as well. As the length of the average drying event increased, CH_4 emissions decreased, and as the length of the average flooding period increased, CH_4 emissions increased. The length to flooding and drying events also interacted with the timing of those events. The South field in 2018 had the lowest cumulative emissions in the study and the longest drying event (30 days), but the North field in 2016 had the second-longest drying event (16.1 days) and mid-range emissions. The longest drying event for the South field in 2018 occurred from late July to mid-August, during the maturation stage when emissions are highest, while the longest drying event for the North field in 2016 between late May and mid-June, during the vegetative stage when emissions are lowest. The North field in 2016 also had the longest average flooding event of all the AWD field-seasons. The soil at our sites is mostly clay, and clay soils take a longer time after a flooding event to develop reducing conditions than silt loam soils (Brye et al., 2013), so longer flooding periods enhance methanogenesis, while interrupting them reduces it.

The yield from water seeded field-seasons for this study was 10.8 and 10.9 t ha^{-1}, which is on the higher end of the range of main season yields for this study, but not significantly higher than the dry seeded field-seasons. In terms of yield, water-seeded rice has been shown to be more prone to lodging than dry seeded rice because the scattering of germinated grains on a wet field can result in higher plant density (Liu et al., 2018). Densely planted rice plants have smaller stem diameters and longer internodes than rice plants spaced more evenly, which increases the chance of lodging and yield reduction (Liu et al., 2018; W. Wang et al., 2021). While this effect was not noted in this study, we also did not carefully assess plant density across all field-seasons of the study. Other studies comparing the yield from water seeded and dry seeded rice had contradictory results, with one study finding that the yield was higher for the dry seeded treatment (Hang et al., 2014), another finding that the yield was higher for the water seeded treatment (Tao et al., 2016), and another finding no difference between treatments (Ko & Kang, 2000).

Some studies have found that irrigation treatments that reduced the overall time the field spent flooded resulted in lower yield, as forms of AWD with long drying periods resulted in water stress, weed growth, and susceptibility to disease (Bidzinski et al., 2016; Carrijo et al., 2017; de Vries et al., 2010; Linquist et al., 2015). Other studies found that AWD treatment had no effect on the yield with respect to DF (Balaine et al., 2019; Carrijo et al., 2018). This study did not find any significant difference in main season yield between AWD and DF.

Rice ratoon cropping is not common in Arkansas and in order to contextualize the yield results we performed a literature review and synthesis of recent rice ratoon studies that reported both main and ratoon yields (Table 8). Guidelines from Texas and Louisiana extension offices say that farmers should expect the ratoon yield to be between 25 to 33% that of the main crop yield, while an overview of international studies found that the ratoon yield could be between 34 and 64% (Saichuk, 2014; W. Wang et al., 2020; Way, 2010). Our own analysis of recent studies in China and Texas found that the ratoon crop could vary significantly, yielding anywhere from 7% to 95% of the main crop (Figure 14). The inconsistency of reported yields suggests that ratoon cropping depends strongly on location and management factors and highlights the need for further research.

Table 8: Range of main crop and ratoon crop yields for each study in the literature synthesis. The majority of studies in this synthesis did not measure CH_4.

Location	**Main crop yield (t ha^{-1})**	**Ratoon crop yield (t ha^{-1})**	**Reference**
Beaumont, Texas, USA; Eagle Lake, Texas, USA	9.21–10.32	3.01–3.66	Dou et al., 2016
Hubei Province, Zhougan Village, China	7.88–9.90	4.05–5.83	Dong et al., 2017
Yunnan Province, Jiupu Village, China	7.32–9.56	2.39–5.71	Chen et al., 2018
Yunnan Province, Jiupu Village, China	4.58–10.05	5.49–8.12	He et al., 2019
Yunnan Province, Jiupu Village, China	6.12–10.56	2.96–6.49	Wang et al., 2019
Hubei Province, Jingzhou, China	5.62–9.46	2.46–4.72	Ding et al., 2021
Sichuan Province, Ziyang, China	7.66–9.08	1.06–1.89	Song et al., 2021
Sichuan Province, Ziyang, China	6.73–9.68	0.55–2.91	Song et al., 2022
Henan Province, Fuji Town, China	6.30–12.12	2.04–4.03	Jiang et al., 2021
Eagle Lake, Texas, USA	5.95–10.63	2.20–6.53	Wang et al., 2021
Henan Province, Xinyang, China	8.3–9.4	3.5-6.6	Zhang et al., 2021

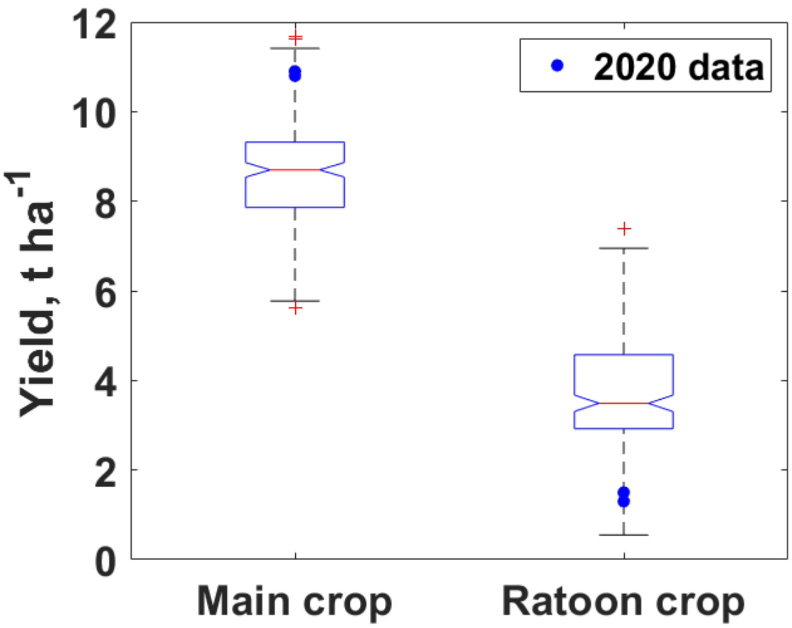

Figure 14: Range of reported main and ratoon crop yields from a review of 199 sites from 11 studies on ratoon cropping in rice (see table 5). The 2020 data is from this study.

The yield from our 2020 ratoon season was within the lower range of plausible values from the literature synthesis, but much lower than would be expected from the guidelines from the extension offices. Ratoon cropping is strongly influenced by timing. In temperate climates, the earlier the main crop is planted, the higher the likelihood of a successful ratoon crop (Dou et al., 2016). By extension, the harvest date of the main crop is also important since it determines the amount of time the ratoon crop will have to mature. Our fields were harvested 3-4 days after August 15, the latest recommended harvest date for ratoon cropping in Louisiana (Saichuk, 2014). October of 2020 was 1.3 °C colder than average, and growth of the ratoon crop may have been slowed during that month by the low temperatures. Experts suggest ratoon cropping with early maturing varieties and planting early enough to avoid the negative effects of late-season cold weather (Saichuk, 2014; Way et al., 2014).

The height at which the stubble of the main crop is cut can also affect the yield of the ratoon crop. Some studies suggest that stubble height should be kept short to induce the plant to produce more tillers, as well as to reduce the pest and disease load (Beuzelin et al., 2012; Way et al., 2014). The general agreement is that moderate cutting heights of 20-30 cm have the highest yield (C. Dong et al., 2020; Torres et al., 2020). The stubble height for this study was 40 cm and that might have been too high to induce sufficient tiller regrowth for higher yields. The stubble height for this study was deliberately cut higher than recommended in order to shorten the regrowth time and increase the likelihood of harvest before first frost (personal communication, Mark Isbell, 2022).

That the cumulative CH_4 emissions from the ratoon crop for this study were higher than the main crop emissions may be due to the main crop being harvested in August. August had the second highest mean and maximum temperatures for 2020. Between the continuously flooded conditions in the early part of the ratoon season, the high temperatures, and the ample substrate for bacterial growth provided by the residue from the main crop left on the field, conditions were favorable for methanogenesis. The ratoon emissions ranged from 39.7 to 50.7 kg CH_4-C kg ha^{-1}, which was comparable to the main crop emissions from other years as in the South field in 2015 and 2020. The yield-scaled ratoon emissions, however, ranged from 30.5 to 33.8 kg CH_4-C ton^{-1} and were greater than all the yield-scaled main season emissions.

Ratoon season emissions in this study were higher than that of the main season, but they were comparatively low when compared to the ratoon studies from the literature synthesis, which showed emissions ranging from 45 to 267 kg CH_4-C ha^{-1}. It is difficult to compare ratoon emissions because they differed greatly between studies (Table 8). Some studies reported higher emissions, with ranges from 50-230 kg CH_4-C ha^{-1} (Xu et al., 2022), or 294-1990 kg CH_4-C ha^{-1}

(Lindau & Bollich, 1993), and rates of 188.62 kg CH_4-C ha^{-1} (Wang et al., 2021). Others reported lower emissions, from 0.59-32.6 kg CH_4-C ha^{-1} (Ding et al., 2021). Overall, the emissions from our ratoon season (39.7-50.7 kg CH_4-C ha^{-1}) fit within the broad range established by other studies. Given the possibility of increasing the ratoon yield and therefore decreasing the yield-scaled emissions, it could be possible to have a profitable ratoon season with yield-scaled emissions in the range of that of a main season under DF management.

5. Conclusion

This study affirmed the results of previous research, that applying an AWD regime to a rice crop reduces CH_4 emissions relative to conventional water management without significantly reducing the harvest yield. Furthermore, we found a significant correlation between the number of days under inundation and field-adjusted cumulative CH_4 emissions. There were also possible relationships between the number and length of drying events and the length of flooding events and cumulative CH_4 emissions, though these relationships were not significant when separated by irrigation treatment, which may mean either that no significant relationship exists or that the drivers of the relationship are different under different irrigation treatments and we have insufficient data to identify them. Further research with additional replicates is recommended. These relationships may be useful for informing model building in the future. With the addition of more field-seasons of data or a different type of model we may be able to estimate emissions with a simple metric such as the number of drying events or the number of days under inundation. The CH_4 emissions increase between the ratoon and main crop was unambiguous but was also based on two field-seasons from a single year, and additional years of ratoon cropping under eddy covariance would be helpful in establishing a baseline for CH_4 emissions from ratoon rice cropping in Arkansas.

We found no difference between yield for different seeding method and irrigation treatments on yield, though as stated previously the water seeding treatments were limited. Given that the ratoon crop was financially viable and ratoon crop emissions were low compared to previous studies in Louisiana, ratoon cropping combined with AWD could be a viable form of sustainable intensification in Arkansas, but it would be more useful if ratoon yield could be enhanced. Yield from the ratoon crop was low compared to the average of other studies from the literature review, and a better understanding of methods to increase ratoon yield without increasing emissions is necessary if ratoon cropping is to be implemented as a sustainable intensification practice.

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