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Supplementary Information for

High nitrous oxide fluxes from rice indicate the need to manage water for both long- and short-term climate impacts

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Text section 1: Farm, agro-ecological region, and seed variety description

(See also SI Figs. S1-S2, SI Tables S2 to S9)

Our study was carried out in three Food and Agriculture Organization (FAO) defined agro-ecological regions (AER) at five farms (farmer managed fields) with a range of flooding regimes (SI Fig. S1) in peninsular India (SI Fig. S2). All of the chosen farms did singlecropping where every year farms were left fallow before or after the rice-growing season. With the exception of an extra subplot (control with no N input) at Farm 4 in AER 8.3, all other farms were divided into two subplots that received one of two treatments, baseline practices (BP) or alternate practices (AP). GHG replicate measurements were made at three wellseparated spots within each subplot.

We note that multiple aeration events similar to what we observed at our study farms are common in both irrigated and rainfed rice farms in India^{[1,](#page-83-0)[2](#page-83-1)}, Pakistan², Nepal^{[3](#page-83-2)}, Bangladesh^{[4](#page-83-3)}, Chin[a](#page-83-4)⁵ and South America as a result of high evapo-transpiration rates, unreliable water/electricity supply, rainfall regimes, soil characteristics, and topography^{[6](#page-83-5)}.

Detailed farm descriptions, seed varieties, weather conditions and treatments are presented in Tables S4-S9.

The rice cultivation alternative practices (AP) were decided via an iterative process involving local NGOs and agronomists. The goal of the iterative process was to find alternative rice farming practices that will *1)* maintain yields; *2)* eliminate or reduce the use of external fossil fuel-dependent inputs such as synthetic fertilizers and chemical pesticides (which in the long term leads to improved health and resilience of agricultural ecosystems and can improve N use efficienc[y](#page-83-6) and input costs); and 3) decrease GHG emission intensity⁷. Yields were estimated from each treatment at maturity after separating grain from the straw and sun drying to a constant weight. Please refer to SI text for more details.

Farms 1 and 2 (AER 3.0): Agro-ecological region (AER) 3.0 is hot and arid, dominated by a short growing season length of $\sim 90 \text{ days}^7$ $\sim 90 \text{ days}^7$. AER 3.0 includes portions of the districts of Bijapur, Bagalkot, Gadag, Koppal, Bellary, Davanagere and Chitradurga in the state of Karnataka, as well as the Anantapur district in the state of Andhra Pradesh^{[7](#page-83-6)}. Seed variety BPT 5204 (parentage GEB-24xT(N)1xMahsuri) used in this AER was developed by Anantapur Agricultural University Rice Research Unit in Bapatla. This variety is resistant to blast and has a yield potential of 5700 kg ha⁻¹ (ANGRAU)^{[8](#page-83-7)}. The amount of inorganic N recommended for this seed variety is 1[9](#page-83-8)0 kg N ha⁻¹ (Efresh)⁹. The results of surveys of conventional farmers are presented in SI Tables S10-S13.

Farms 3 and 4 (AER 8.3): This AER is characterized by a hot semi-arid ecosystem with a growing period of 120-150 days and includes the Chittor district of Andhra Pradesh, and Vellore, Dharmapuri, Salem, Cuddalore, Chengalpattu, Periyar, Kanchipuram, Erode, Tiruchirapalli, Pudukkottai and Tuticorin in the state of Tamil Nadu^{[10](#page-83-9)}. Average annual rainfall range in this AER is 550-[10](#page-83-9)00 mm¹⁰. At this farm, AP and BP plots were separated by a 9 m wide fallow area. Seed variety ADT 39, used in this AER, with parentage IR8/IR20 was developed at Tamil Nadu Rice Research Institute Aduthurai with a potential yield of 5800 kg ha⁻¹ (RKNP)^{[11](#page-83-10)} and average yield of 5000 kg ha⁻¹ (TNAU)^{[12](#page-83-11)}. It is a semi-dwarf variety suitable

for irrigated low lands, resistant to blast and sheath rot) 11 with a blanket recommendation of 150 kg ha⁻¹ of inorganic N which applies to all seed varieties grown in this state^{[13](#page-83-12)}. The results of surveys of conventional farmers are presented in SI Tables S14-S21.

Farm 5 (AER 8.1): This AER is characterized by a hot semi-arid ecosystem with mixed red and black soils and a growing period of $90-120 \text{ days}^{10}$ $90-120 \text{ days}^{10}$ $90-120 \text{ days}^{10}$. The region receives an annual average rainfall of 800-1[10](#page-83-9)0 mm¹⁰, while the Tirunelveli district receives an average annual rainfall of 879 mm (District Groundwater Brochure). The ASD 16 seed variety, used in AER 8.1, has a parentage of ADT 31/CO39, and was developed by the Rice Research Station of Ambasamudram. It has an average yield of 5600 kg ha⁻¹ (TNAU)^{[12](#page-83-11)} with a recommendation of 150 kg ha⁻¹ of inorganic N which applies to all seed varieties grown in this state^{[13](#page-83-12)}. The results of surveys of conventional farmers are presented in SI Tables S22-S23.

Text section 2: Estimation of C & N content of organic inputs (Tables S4-S9)

The range of percentage C in different organic inputs presented in Table 1 (and utilized in our regression analysis) is based on maximum and minimum values reported in published literature (see Tables S4-S9 for range of % C in specific inputs)^{[7,](#page-83-6)[14-17](#page-83-13)}.

Except Azolla, biofertilizer used on Farm 3 in 2012 (SI Table S6), the percentages of total N in organic inputs is a fixed value based either on measurements performed as a part of our initiatives in India or as reported in regional published literature (see Tables S24-S29 for % N in specific inputs)^{[18-21](#page-83-14)}. All of the N content in any organic input is not labile. In addition, the labile N in organic inputs added at a given point of time mineralizes slowly over a period of \sim 3 years^{[22](#page-84-0)}. Thus for every rice-growing season, cumulative available N (or mineralized N) contributed by organic matter was influenced by OM added over three years (the season of interest plus the two preceding rice-growing years). The % organic N mineralized during a fixed time interval depends on seasonal temperature, soil properties, microbial activity, etc^{[23,](#page-84-1)[24](#page-84-2)}. In the absence of any regional measurements of mineralization rates of organic N, we used three different sets of mineralization percentages (% total organic N mineralized in the first (that is, year of) and second, and third years (after) the addition of organic matter) to calculate the maximum and minimum N content utilized in our regression analysis (Table 1, Main text). One set of N mineralization rates (13%, 7.0% and 5.5%, respectively, in the first, second, and third year after application) was based on the Uchida model developed for Japan^{[22,](#page-84-0)[25](#page-84-3)}. Another set of mineralization percentages (45%, 20% and 10%) were based on studies made by several agricultural extension centers in the Unites States^{[23,](#page-84-1)[26](#page-84-4)}. The third set of mineralization percentages (10%, 40% and 15%) were based on local expert advice which suggested that if farmers add organic inputs every third year in peninsular India for both non-rice and rice crops, they get maximum yields in the second year after application of organic inputs. Additionally, it was suggested that, in peninsular India, yields are significantly lower during the year of organic application and during the third year after the organic application. We are not in a position to evaluate which of these mineralization rates is best applicable to our farms and hence present the minimum and maximum possible mineralized N available due to addition of organic inputs at all farms in Table 1.

While some organic inputs (e.g., FYM) are known to immobilize mineral N^{24} N^{24} N^{24} , we did not have a systematic way to take this immobilization effect into consideration.

Text section 3: Water index (cumulative water levels) & impact of drainage

A field water tube (FWT) is a 40-cm-long perforated tube inserted 20 cm into the soil next to each sampling chamber. Field water tube water levels were linearly related to soil moisture (\mathbb{R}^2 > 0.9) and the soil moisture levels when the fields were flooded at soil level were directly related to soil % clay or water holding capacity ($R^2 = 0.7$ or 0.8, respectively).

With the exception of farm 3 (SI text section 3), FWT level observations (on days when fields were irrigated) were made right before the beginning of irrigation for the day. At Farm 3, the field water tube water level was observed 1-2 hours after irrigation on the same day. Therefore, we corrected the observed water level data by subtracting the average reduction in water levels over ~24 hours at that Farm in the season of interest from the observed value. The average reduction in water levels was calculated by averaging the decrease in water levels between a day when irrigation was done and the following day when no irrigation was done.

Significant CH⁴ and N2O emissions are associated with drainage (i.e., water level less than -7.5cm and/or $\langle 0 \rangle$ cm after $>$ 5 days of flooding) both between and at the end of a growing season (SI Tables S30 and S31 and SI Figs. S3-S14). It is quite likely that our data has not captured coincidence of drainage and high N2O flux for some days/seasons (especially at Farm 3) because the water levels presented in this study represent a snapshot taken once a day.

We note that if the soil is sandy, the irrigation frequency will need to be higher to maintain a given level of water index as compared to clayey soils. Therefore, water index implicitly captures some of the impact of soil texture on GHG emissions.

Text section 4: N2O emission rate measurement & importance of high intensity sampling

The reliability of direct N₂O flux measurements depends on a sampling design that captures spatial and temporal variability^{[27](#page-84-5)} (See SI Figs. S3-S14 and Tables S2- S3 and S43). We infer that the reason that high N₂O fluxes were not detected in earlier studies is twofold. Since the early 1980s when the first set of rice GHG measurements were made^{[28](#page-84-6)}, most studies were conducted within long-term research stations at well-irrigated and continuously flooded plots. It is well established that redox conditions of flooded paddies are conducive for methanogenesis but not for nitrification-denitrification. According to our analysis, continuously flooded rice fields will have a high water index (i.e., >150 cm) and very low N₂O emission rates. In contrast, our work was done on farmer managed fields in varying soil conditions with a range of conventional and alternate water and N management regimes that were/are actually followed by farmers in the respective agro-ecological zones (Figs. S2 and S3). More importantly, very few studies to date have employed a field sampling intensity sufficient to accurately describe N_2O emission rates given the high temporal variability in N_2O flux (which is usually much higher than what is required to capture seasonal CH_4 emissions) (Tables S1 and S43). About 40 recent studies done in India to measure rice GHG emissions and, except one, all of them have a sampling intensity of less than 22% (Average sampling intensity = $12\% \pm 6\%$ Standard Deviation). The Indian study which had the highest sampling

intensity (36%) also had the highest N₂O emission rate (1.4 tCO_{2e100} ha⁻¹ season⁻¹, SI Table S1).

Nitrous oxide emission rate measurement methodology: We note that our complete sampling and analysis methodology has been previously published^{[27](#page-84-5)}. Briefly, manual closed chamber based air sampling followed by detection by a gas chromatograph (Thermo Fisher Trace GC 600) was used to quantify N₂O and CH₄ emission rates. Field sampling for N₂O flux measurement was performed on 35-65% of the days, with a minimum of twice a week sampling and daily sampling for 3-5 continuous days after all "events" e.g. sowing, fertilizer application, irrigation, rainfall and weeding. Manual chambers (50cm*50cm*40cm) were deployed on anchors (also referred to as base-frames) with a water trough to receive the bottom of the chamber. After 50 to 70 days of rice growth, it was necessary to vertically stack two chambers to keep the plant from being bent (or getting distorted) during sampling. Since the ambient temperature in our study areas could get as high as 45° C and chamber temperatures routinely increase by up to 10^{0} C over the course of half hour sampling period, all calculations were corrected for temperature changes and temperature increase did not create gradient of GHG concentration within chamber's headspace volume.

Trace GC 600 (Thermo-Fisher Scientific, USA) is a dual channel, packed column GC with ECD, FID and thermal conductivity detectors (TCD). Altogether, the three Porapak Q columns (1/8" stainless steel outer diameter, 2mm inner diameter, 80–100 mesh size, Restek catalogue number #PC16737) separated the sample components at 60°C isothermal oven temperature. One channel consisting of a 1m long pre-column and a 3m long main analytical column separated and detected N₂O on ECD with 10 mCi strength $Ni⁶³$ as electron source while the other channel with a 3m column detected CH⁴ on FID.

The GC was calibrated every day with four standards: 0.197, 0.393, 0.795 and 1.615 ppmv N2O (Bhuruka Gases, Bengaluru; NIST certified at 2% RSD). Concentration (in ppm) at each time point, as measured by GC, was converted to a mass equivalent (in µg) using ideal gas equation and corrected for temperature, chamber volume and pressure. Daily flux rates were calculated as follows

 $G_t = C * V * M * P / R * T_t$ $F = [\Delta Gt / \Delta t]^* 60*24/A$

Where:

- t Time (in min)
- G_t concentration of GHG at time t (μ g L⁻¹)
- C concentration of GHG (ppmv)
- V Chamber headspace corrected for plant volume (L)
- M molecular weight of GHG: 44 g.mol⁻¹ N₂O; 16 g g.mol⁻¹ CH₄
- P pressure corrected for elevation (atm)
- R universal gas constant (0.0820575 L atm . K . mol)
- T_t chamber temperature in K at time t (= temperature in ${}^{\circ}C + 273.15$)
- F total daily GHG flux in μ g. m⁻². d⁻¹
- A area sampled (base-frame footprint) (m^2)

The minimum detectable N₂O flux was determined to be 28 ppb h^{-1} ⁽ based upon a 30 minute) chamber deployment period, four sampling points under linear regression, and RSD of 2% (Parkin et al. 2012). That translates to to \sim 15 µg N₂O m⁻² h⁻¹ for our chambers with an volume of ~100L, ambient temperatures in the range of $35-45^{\circ}$ C and base-frame footprint of 0.25m². Following the recommendations of GRACEnet protocol (Parkin and Venterea 2010), we reported the actual measured value even if it falls below the MDL. For values above MDL, the linearity of increase in concentration of GHG over time was monitored and slopes with (coefficient of determination) R^2 values less than 0.85 were not included in cumulative seasonal emission. Cumulative N2O emission for the entire cropping season was computed by plotting the daily flux against the days of sampling, calculating the area covered under the plot by linear interpolation (i.e., by adding the areas of trapeziums formed by the daily flux rates; see below for further discussion). Cumulative emissions were calculated separately for each replicate plot before calculating the average emissions for BP and AP. Negative emissions were dealt in the same way as positive emissions. The details of the design of Perspex chambers and baseframes, sample storage, GC optimization and daily calibration, data analysis have been described elsewhere (Tiwari et al. 2015).

Linear interpolation: When sampling frequency is lower, linear interpolation can results in both substantial over and under-estimation of cumulative seasonal GHG emission (especially for N_2O which exhibits much higher temporal variation than CH_4). This occurs when the spikes in N2O, which usually occur following fertilization and/or rainfall or drainage, are not captured by the field sampling or more commonly, when either the rise or decline of N2O peak is not fully captured by the field data.

N2O emissions generally exhibit peaking behavior and the peak flux decay is usually exponential which has led to concern over the use of linear interpolation / trapezium method (see Tiwari et al 2015 for references)^{[27](#page-84-5)}. Even when the sampling frequency is adequate in general (>40% of the crop growth days), it is possible that no (reliable) samples are available at a few critical times (e.g., right before or after a N_2O emission peak). To deal with such rare cases, we used the following strategy: when the decline of a N2O emission peak with a height greater than 10 times the MDL (i.e. $>200 \mu g h^{-1} m^{-2}$) was not captured by field measurements, the spikes were decayed to MDL levels (or the available measured data) by adopting a best-fit exponential equation for each spike. When possible, number of days needed for an emission spike to "come down" to MDL levels were derived from other measured peaks for the same crop and replicate treatment. While this strategy is far from perfect and is subjective, we think it might be more reasonable than linear interpolation for N2O peaks. Please see more details in Tiwari et al (2015). In general, we found that linear interpolation overestimated the flux by 50- 100% as compared to 1) exponential decay of the peak value and 2) a "least possible emission approach" where a constant value, which was equal to the least measured flux rate immediately before or after the gap period was presumed for all days in the "gap period". The extent of over-estimation depended on the a) length of gap period and b) the height of the peak. The emissions estimated by the "least possible emission" approach was lower than the estimated emissions calculated with the "exponential curve method".

Text section 5: Factors influencing N2O emissions

We don't have pre-treatment information for our plots before the seasons we studies them and cannot be entirely sure how much different locations at single farms varied before intervention.

Influence of inorganic N input on N₂O flux: Ultimately, N input is necessary for nitrous oxide production, be this from existing soil pools or from organic or inorganic fertilizer input.. However, unless the paddy soils have the right redox conditions and right range of water filled pore capacity, N2O is either not produced or is consumed. Why? When farms are truly flooded and oxygen content of soils is low, ammonia doesn't nitrify and no substrate is available for denitrification. Also, the last step on denitrification which converts nitrous oxide to dinitrogen gas is highly oxygen sensitive. When fields are flooded and there is close to no oxygen in the soils, nitrous oxide converts to dinitrogen (if there is sufficient organic matter to support microbial activity). Lastly, if the farm remains flooded for an extended period of time after fertilization, N is converted to into organic forms which are much less amenable to denitrification even after intermittent flooding is introduced later in a rice cropping period (SI Figure S18).

Influence of organic matter addition on N2O flux: Suppression of N2O? When inorganic N is added without simultaneous addition of organic matter, a N2O peak emerges within an average of 4 (range 0-12) days after the addition of inorganic fertilizer and N_2O flux remains high for an average of 10 (range 1-21) days after fertilization. However, in several cases where a large amount of organic inputs were added at the beginning of the season (e.g. Farm 2, Farm 3 [2013] and Farm 4), no N2O was seen until very late in the season. Furthermore, when the added N is either exclusively from organic inputs or from both inorganic and high organic inputs, a peak emerges later and stays higher over a longer period of time as compared to when the added N is exclusively in the form of inorganic N. With the addition of inorganic N, N_2O flux remains high an average of 16 (range 9-28) days relative to after addition of organic N with N₂O flux remaining high for an average of 34 (range 11-92) days after fertilization (SI Table S30) (SI Figure S20).

Influence of soil texture (%clay to %sand ratio) on N2O flux (SI Figure S22): The high correlation coefficient found for clay/sand ratio $(R = 0.63)$ suggest that soil texture characteristics could play a role in the level of N_2O emissions. However, when added to the multivariate regression model, soil texture did not explain any additional variance and was dropped from the model. This could be a consequence of the water index, which explains most of the variance in emissions at the farms. For a larger sample size, with greater variability in soil characteristics (e.g., clay/sand), it would be expected that soil characteristics would appear as a parameter that explains variance in N_2O emissions. The maximum global clay/sand ratio is 94 (data not shown), while for the sampled dataset the ratio is 0.1-0.44. This wider range of higher clay content illustrates the need for future work that analyses the relationship between high clay/sand ratios and N₂O emissions.

Text section 6: Factors influencing CH⁴ emissions

Methane is a microbial end product of labile organic matter decomposition under anaerobic soil conditions (at a redox potential or Eh close to -150 mV). The soil redox state is influenced by the water levels, soil texture and Eh-pH buffering capacity of the soils and the concentration of labile organic substrates that changes with rice variety (which controls the extent of root exudation, and dead and decaying roots and plant litter at different crop growth states) as well as the timing and type of added organic fertilizers and crop residues. From negligible values at the beginning of the season, CH⁴ emissions generally show a continuous gradual rise during the vegetative phase correlating with increasing plant biomass, peaking near panicle differentiation, a period of rapid root development^{[28](#page-84-6)}. While there were high CH₄ emissions during multiple growth stages at different locations (SI Table S31), we did not clearly observe the phenomenon of continuous gradual rise in CH⁴ except at Farm 2 for two BP replicates. This is likely because fluctuating water levels disturb soil redox conditions, a phenomena which is not conducive for continuously increasing CH⁴ flux. Instead, we observed clear evidence during multiple seasons that drainage events triggered CH4 fluxes (SI Table S31) which are different from end-of-season drainage-related GHG emissions that have been documented earlier^{[29](#page-84-7)}. We surmise that both mid-season and end-of-season drainage triggers a sudden release of CH4 when the soil was drained enough to allow CH4 to escape directly to the atmosphere.

Impact of organic matter application rates on CH₄: The highest CH₄ fluxes from continuously flooded rice farms are recorded in fields with high OM inputs^{[28,](#page-84-6)[30](#page-84-8)}. We observed a positive correlation of rice-CH⁴ with soil organic matter (SI Figure S28) but not between CH4 and organic matter inputs (SI Figure S27).This lack of effect of OM inputs on farms with lesser flooding has been previously reported 31 and likely results from reduced flooding oxygenating soils and producing unfavorable redox conditions for methanogenesis, irrespective of OM application.

Range of hourly CH⁴ emissions are high but seasonal fluxes are low: Our maximum hourly CH₄ fluxes are higher (18.5-125 mg CH₄ m⁻² h⁻¹ [SI Figures S9-S14] *vs* 20-58^{[28,](#page-84-6)[31](#page-84-9)} mg m⁻² h⁻¹) but the cumulative seasonal fluxes are lower $(-1-336)$ [Table 1 and SI Table [31](#page-84-9)] *vs* 954-1550^{[28,](#page-84-6)31} kg ha⁻¹) than previously reported across the world. This is likely because 1) our high resolution sampling captured low CH⁴ fluxes between high flux periods which when interpolated decrease the net seasonal flux (SI Figures S9-S14) and 2) intermittently flooded paddies have lower emissions than constantly flooded paddies 28,31 28,31 28,31 28,31 .

Text section 7: Recommendations for lowering climate impacts of rice

Here we present generalized recommendations for integrating (simultaneously using) multiple "good" production practices on the basis on local soil/weather conditions that could reduce net climate impacts of rice. Based on our in-depth analysis of GHG emissions at each farm, we offered the following general recommendations to farmers in the study region. Without regionspecific studies that confirm that these recommendations will hold in a new region, application of these recommendations to new regions outside of study area might not yield desired climate benefits.

- Keep water index for the whole season between -250 and 250 cm (mild intermittent flooding) such that flooding is shallow.
- Limit the number of times water stays above soil level for more than 3 days.
- Add as little inorganic N as really necessary to maintain crop yields. For regions that remain intermittently flooded, add inorganic N in split doses right before a flooding event.
- Don't let the fields drain too much and keep water levels above -5 to -7 cm during the growing season (except close to harvest)
- For farms like Farm2, Farm4 and Farm5 where water likely does not percolate down quickly (or water index is high), reduce organic matter use to reduce CH⁴ emissions.
- For farms like Farm1 or Farm3 where water likely percolates down quickly (or water index is low), higher amount of organic carbon can be added to reduce N_2O emissions without increasing CH4 emissions.

Text section 8: Limitations of our geospatial extrapolation

Empirical models vs. biogeochemical model: Given difficulties and resource-intensiveness with field measurements, GHG mitigation programs across the world have always looked to modeling-based approaches for quantification to GHG emission reduction. There are two types of modeling approaches used:

1. Empirical models. Regression analysis is used to extrapolate existing research and data to develop regionally explicit emissions factors. The regression equations produce GHG response curves for different management impacts (or for just nitrogen input for Tier 1 models). They can be specific to conditions at the ecozone (or agro-ecological region). They can be developed without the use of a complex model (which is usually much more input data-hungry) and are relatively easy and transparent to use. They do not capture the effects of spatial and temporal variability on GHG dynamics at finer scales, and can be less flexible in handling variable management combinations.

2. Process-based biogeochemical models. These models use mechanistic equations based on substantial long-term research to represent growth, nutrient, water, soil, and GHG dynamics. The models can be used in two distinct ways:

a. At a regional (Tier 2) scale, covering area with similar soils and climate, to produce reasonable, regionally sensitive emissions factors that can be used to develop a protocol or program accounting methodology. This approach can be relatively simple, transparent, and low-cost. However, using models at this scale may not reflect the spatial/temporal variability of GHG dynamics at a particular local site in the region.

b. At a farm or project (Tier 3) scale which can be used for a quantification tool within a protocol or program accounting methodology. At this scale models can capture fine-scale variability and dynamics but require significantly more site-level data inputs and detailed verification.

DNDC and Daycent are the two current process based biogeochemical models that predict rice-CH4. The current Daycent model only predicts methane; nitrous oxide emissions are not estimated. We have confirmed with DNDC development team (William Salas, Applied Geosciences, Personal communication) that they have published no other report that uses DNDC to predict global nitrous oxide emissions from rice farms other than the study we have already cited. Other DNDC based studies are limited to one field or one small geographic area.

The use of multiple regression based empirical models is not new in the field of agricultural greenhouse gas mitigation. Many GHG emission reduction protocols, including those being approved the state of California for agricultural C offset programs and many other International carbon registries like VCS or Gold Standard, use empirical models to predict agricultural GHG emission reductions. We note that IPCC still uses Tier 1 simple and universal equation to determine N_2O emissions from upland (non-rice) crops. Our results were used to develop a multiple regression derived Tier 2 empirical model with multiple parameters for extrapolation which we consider to be better than the IPCC Tier 1 emission factor for the Indian subcontinent.

Our robust measurements at individual farms show large differences between treatments (AP vs BP). We do note that we don't have information on GHG emission rates from our study plots before the study period and it is possibile that different locations at single farms significantly varied with respect to soil biogeochemistry (and thus GHG emission rates) before our study began and different treatments were applied to different subplots.

We understand that extrapolating our model based on five farms to other rice growing regions in a subcontinent should be done with significant caution. We are encouraged, however, to present our extrapolated results because one of the previous reports^{[32](#page-84-10)} to give an estimate of global or regional rice nitrous oxide emissions includes assumptions that are coarser than some of our assumptions (e.g., geospatial N or extent of flooding, see below) and is based on an even more limited empirical rice-N2O dataset, at least for the Indian subcontinent (see SI Table S1 for a compilation of existing Indian rice GHG studies).

Extrapolating our regression outputs at a large scale for this GIS analysis entails making a series of assumptions and using standardized datasets. As such, there are several constraints to consider when interpreting these maps and resulting rice-N2O risk assessments.

Inorganic fertilizer input dataset: The data documented in Mueller et al. (2012) depicts application rates standardized to the year 2000^{33} 2000^{33} 2000^{33} . Although this is the most recent globally consistent and spatially referenced data, application rates will have increased (and perhaps significantly so) in the last 16 years. This aspect may therefore shift relative risks to be higher in regions where increases in N application rates during this period have been greater than average.

Seasonal changes in water levels: Another key aspect for consideration is the concept of seasonality. In many parts of the world, rice is farmed over two (and sometimes three) consecutive seasons in a single year. We were limited by our inability to differentiate between rice vs rice-rice cropping cycles. Additionally, fertilizer inputs from Mueller et al. (2012) describe total annual (and not seasonal) amounts. Thus, there may be regions in the Indian subcontinent where our estimates are less accurate due to the need to better standardize water indices for single- *vs* double-cropped paddies.

Water index and frequency of flood events: The range of hypothetical values for the water index and number of flooding events for each rice management system is based on an informed opinion. Ideally, a preferred approach such as remote sensing would be used to impute typical values. Field water tube measurements vary greatly across time and soil types. As an integral of this, the water index (cumulative water level) variable is sensitive to these fluctuations.

However, appropriately extracting a remotely sensed record of both water index and flood events is not feasible for several reasons. First, while critical soil characteristics such as water retention are known, the frequency of irrigation events in rice paddies is not documented in a standardized manner. Second, water table depth in fields cannot be reliably assessed through remote sensing at a high enough frequency. With 30m x 30m imagery, LANDSAT potentially has a high enough resolution to accomplish this, yet lacks the appropriate coverage and temporal frequency to capture daily changes in water levels. MODIS, while having had some measure of success in mapping flooded rice paddies^{[34-38](#page-84-12)}, does not have a high enough spatial resolution to be calibrated and validated to our field data, which in all cases were sub-0.25 km² plots. Further challenges are presented by cloud contamination and regional differences in normalized reflectance indices such as LSWI (land-surface water index) that would indicate flooded paddies.

Extrapolation beyond the range of empirical data: The geospatial extrapolation is applied to regions where the range of values for all variables (inorganic N use rates, water indices, number of flooding events) spans a wider range than that which was obtained empirically from our field studies and in turn, the dataset that generated regression results. This extrapolation relies on the assumption that N2O emissions scale linearly beyond this range. There is no evidence that would allow us to characterize this relationship as nonlinear or otherwise, however it is quite likely that there are important nuances not captured by our analysis.

Text section 9: Temporal estimation of cumulative radiative forcing

Assessing the combined climate implications of different GHGs is challenging because their effect is time dependent. In the case of rice cultivation systems, emissions from both CH⁴ and N_2O — a short-lived and a long-lived climate pollutant, respectively — require that the climate implications are analyzed as a function of time, and not as snapshots at particular years after the emissions took place.

By looking at the cumulative radiative forcing over a continuous timeframe, it is possible to observe offsets in which reductions/increases of one climate pollutant have different climate impacts at different points in time. This temporal dimension of radiative forcing highlights the importance of an integral management that focuses on reduction of both short-lived and long-lived climate pollutants^{[39,](#page-84-13)[40](#page-85-0)}.

The commonly used method of comparing different climate pollutants through global warming potentials (GWP) compares a given GHG against CO2, which requires an arbitrary selection of a time horizon. The most commonly used time horizon is 100 years, which undermines the climate impacts of short-lived pollutants such as CH⁴ in the near term. Reporting the implications of specific mitigation options over both the short-term GWP (20 years) and long-term GWP (100 years) gives a more complete picture of climate impacts^{[41](#page-85-1)}. Nonetheless, the only way to completely depict the trend and offsets of more than one GHG emitted by the same system throughout its lifetime is to visualize the cumulative radiative forcing as a function of time.

As an additional challenge, GWP establishes a direct comparison to CO₂. This is useful in order to compare total emissions from different systems (e.g., agriculture *vs* energy). However, within the rice cultivation system, there are no significant $CO₂$ emissions. Thus a framework that allows a more direct integration of the GHGs of interest (CH⁴ and N2O) simplifies the analysis of adequate management and emissions reduction scenarios.

Here we use the technology warming potentials (TWP) framework developed by Alvarez et al.^{[42](#page-85-2)}. This framework was originally used to analyze the climate implications of the natural gas system and different natural gas fuel-switching scenarios. We extend this analysis to rice cultivation systems by estimating the cumulative radiative forcing of different management practices.

The TWPs at each point in time represent the ratio of cumulative radiative forcing from two different management practices. The choice of the denominator could be seen as a base case of emissions or a benchmark used to compare against a switch in management practices. Thus, the TWP used to compare CH⁴ and N2O emissions from two management practices could be expressed as:

$$
TWP = \frac{E_{1,CH_4}TRF_{CH_4}(t) + E_{1,N_2O}TRF_{N_2O}(t)}{E_{2,CH_4}TRF_{CH_4}(t) + E_{2,N_2O}TRF_{N_2O}(t)}
$$
(Equation S1)

where $E_{i,j}$ represents the emission rate (in kg ha⁻¹) of climate pollutant *j* from management practice *i*, and $TRF_j(t)$ represents the total radiative forcing values of each pollutant *j*. Estimation of emission rates and selection of management practices scenarios are discussed below.

Derivation of $TRF_j(t)$ values is provided in Alvarez et al.^{[42](#page-85-2)}; our main set of results assumes that both climate pollutants are emitted continuously and indefinitely at a constant rate, $E_{i,j}$. In this case, TRFs needed in equation S1 can be expressed as:

$$
TRF(t) = \int_0^{t_{max}} \int_{t_E}^t REf(x, t_E) dx dt_E
$$
 (Equation S2)

where RE represents the radiative efficiency of the gas. Direct radiative efficiency is $3.6 \times$ 10^{-4} Wm⁻²ppb⁻¹ for CH₄ and for 3.0×10^{-3} Wm⁻²ppb⁻¹ N₂O^{[43](#page-85-3)}. Following the IPCC convention, we include the indirect effects for both climate pollutants. For CH4, the direct RE is enhanced by 50% and 15% to account for indirect forcing due to ozone and stratospheric water, respectively; resulting in 6.0×10^{-4} $Wm^{-2}ppb^{-1}$. For N₂O^{[43](#page-85-3)}, the indirect effects decrease RE to 93% of the direct effect resulting in 2.8×10^{-3} $Wm^{-2}ppb^{-1}$.

The inner integral in equation S2 sums radiative forcing from the year in which the gas was emitted (t_E) to year t. Similarly, the upper bound in the outer integral, t_{max} represents the maximum time of emissions. In our case we examine emissions for the first 200 years.

Finally $f(x, t_E)$ represents the exponential decay of both pollutants in the atmosphere:

$$
f(t, t_E) = e^{-\frac{t - t_E}{\tau_M}}
$$
 (Equation S3)

where τ_M is 12.4 years for CH₄ and 121 years for N₂O.

Assumptions about rice cultivation management practices (for Figure 3)

SI Table S39 summarizes the different hypothetical management practices that we considered for our temporal radiative forcing analysis. As shown in the multiple regression analysis, a given set of flooding conditions affects CH⁴ and N2O emissions inversely. The selected management practices represent a wide spectrum of flooding conditions that allow us to assess the implications of different levels of emissions of the two climate pollutants.

Because the flooding conditions (water index and number of periods of continuous flooding>3 days) explain the majority of the variance for both pollutants, for this analysis we only focus on their changes, leaving the other inputs (e.g., SOC and inorganic N input) fixed.

To analyze the climate implications from different management practices, we plot the ratio of cumulative radiative forcing (Equation S1) as a function of time, leaving the CH⁴ and N₂O emissions constant and looking at the time-dependent offsets. When looking at the results, values below one represent climate benefits (lower cumulative radiative forcing than the basecase); while values above one represent adverse climate implications relative to the base-case or denominator. In our analysis we select two management practices as denominators in Equation S1.

Explanation of Figure 3 in the main paper We established irrigated continuous flooding scenarios as the base case (red dotted line, Fig. 3A) where high water index and elevated number of flood events>3 days result in zero N₂O emissions and high CH₄ emissions. Thus, other water management practices represent choices that tend to reduce CH₄ emissions while triggering N2O emissions. Intense-intermittent flooding scenarios cause an initial reduction of CH_4 emissions with an initial reduction of \sim 50% of the relative cumulative radiative forcing during the short term, however, this management practices increase N_2O emissions which offset the net climate benefits significantly eroding the initial climate benefits after ~150 years.

Switching from continuous to medium- or mild-intermittent flooding for water management also underscores the long-term effect of N_2O emissions. The exact extent of climate benefit over the base case of continuous flooding will depend on the exact nature of water management (water index and flood events).

Text section 10: Change in emission factors for Indian rice systems

Our high resolution data updates both rice CH4 and N2O emission factors for rice farms with intermittent flooding as well as upland/drought-prone rainfed farms. A recent research study by the Indian government^{[44](#page-85-4)} updates India's last submission to United Nations Framework Convention on Climate Change^{[45](#page-85-5)} with respect to agricultural emissions. According to this study^{[44](#page-85-4)}, ~18 million ha of rice is grown under intermittent flooding and ~14 million ha under drought-prone rainfed or upland rice systems emitting $0.03-66$ kg CH₄ ha⁻¹ but no N₂O (see Table 2 in Bhatia et al, 2013). Our high resolution measurements show that CH⁴ emissions from baseline intermittently flooded farms are significantly higher at \sim 120 CH₄ kg ha⁻¹. In addition, baseline intermittently flooded farms and those with water index >-1000 cm show rice-N₂O to be an average of >9 and >14 kg N₂O ha⁻¹, respectively. Even without any changes in CH₄ emissions from upland or drought-prone rainfed paddies, these corrections add \sim 125 million tCO_{2e100} to the total Indian rice GHG budget (see below), at the least a 100% increase

over the 120 million tCO₂e₁₀₀ year⁻¹ estimate presented by the government^{[45](#page-85-5)} (at CH₄ GWP₁₀₀) $= 34$).

Our new estimate for intermittently flooded paddies:

- N₂O emission from intermittently flooded paddies = 18 million ha year^{-1*9} kg N₂O ha⁻¹ ¹*0.298 tCO₂e₁₀₀ kg⁻¹) = 48 million tCO₂e₁₀₀ year⁻¹.
- CH₄ emission from intermittently flooded paddies = 18 million ha year *120 kg ha^{-1*}0.034 tCO_2e_{100} kg⁻¹) = 73 million tCO₂e₁₀₀ year⁻¹.
- Total GHG emission from intermittently flooded paddies $= 74 + 48 = 122$ million tCO₂₀₁₀₀ year-1
- The original estimate for intermittent flooding by the government^{[45](#page-85-5)} is 775 Gg CH₄ which equals 26 million tCO₂e₁₀₀ year⁻¹ which makes the increase due to intermittently flooded paddies = $122 - 26 = 96$ million tCO₂e₁₀₀ year⁻¹.

Increase due to drought-prone rainfed and upland paddies: We did not measure climate impacts of rice cultivation at upland or drought-prone rainfed paddies. However, our findings show clear impact of reduced flooding (which increases drying and wetting cycles) on rice-N₂O (Equation 1 in the main text). While not flooded as much as our experimental farms, upland and drought-prone rice systems do experience several drying and wetting cycles. When we use half the rate of N2O fluxes seen at our least flooded farms as a conservative estimate of N₂O fluxes from upland or drought-prone farms, we add 29 million $tCO_{2}e_{100}$ year⁻¹ to climate impact of Indian rice cultivation.

14 million ha year^{-1*} 14 kg N₂O ha^{-1*} 0.5^{*} 0.298 tCO₂e₁₀₀ kg⁻¹ = 29 million tCO₂e₁₀₀ year⁻¹.

Hence, the total increase as compared to previous estimates will be $125 (= 96 + 29)$ MMT tCO_2e_{100} year⁻¹.

Text section 11: Importance of measuring soil carbon

We note that the net climate impact of rice is the combined effect of CH₄, N₂O and soil C loss (or gain) (e.g., $GWP_{100} = 31*CH_{4} + 298*N_{2}O + 3.66*[soil C loss]$), and soil organic content affects soil health and long-term rice productivity. Because soil C sequestration potential for flooded rice farms can be significant^{[46-48](#page-85-6)} and low N use, reduced flooding and/or low organic matter use can decrease that potential, we recommend long-term measurements of soil C at rice farms concurrent with CH_4 and N_2O flux measurements.

All SI Figures

All figure legends are below the figure. In case of some multi-part figures, a general description of the figure is presented above the figure.

Figure S1: Definition of flooding regimes in this study. The primary determinant of a flooding regime, according to this classification, is water index. It is a measure of cumulative extent of flooding and is the sum of daily water levels in a vertical field water tube. Flood events>3 days, another water-use variable, is the number of times a plot had flooding (>0 cm water level) for more than 3 days and described the number of multiple aeration events for a given water index. As water index decreases, the cumulative flooding at a given farm will decrease. The actual extent of water used to maintain a given water index at any location will be a function of soil texture and local evapo-transpiration rates. As the water index decreases, number of practically allowable long flood events (that are over 3 days long) decrease. This is because as number of long flood events increase, the burden of reducing water index to negative values falls on lesser and lesser number of non-flooded days. We define reduced flooding as either medium-intermittent flooding or intense-intermittent flooding. Alternate wetting and drying usually advocated to reduce CH⁴ emissions includes allowing water to drop down to 15 cm below soil level and roughly corresponds to our medium-intermittent flooding regimes.

For a given range of water index, when there are more continuous flood events that are >3 days in duration, shorter duration flooding (<3 days) is less frequent. This reduces the number of multiple aeration events which can reduce N2O fluxes while increasing chances of higher CH⁴ emissions. The number of flooding events in wetland/deepwater systems could be just one but our equations 1 and 2 might not apply well to such systems. A key difference between upland and intense-intermittent flooding regimes is the degree of saturation of the root zone of the rice plant. With an average maximum root depth of 15 cm, intense-intermittent flooding keeps the rice plant's root zone much more flooded than upland systems. Mid-season drainage (-20 cm for 7-8 days) implies a net water index of 100-450 cm.

Fig. S2: Approximate locations of experimental farms (see dots) and the Indian agroecological regions (AER) included in this study. Farms 1 and 2 as well as Farms 3 and 4 are very close to each other. The exact GPS location of each farm is presented in SI Table S2.

See next fourteen pages for Figs S3-S8 and S9-14

Figs. S3-S8: Temporal variation in N2O at all farms. The X-axis on these graphs indicates the day after transplantation. The primary Y-axis presents GHG emissions in units of mg m-2 h -1 (in black closed circles). The secondary Y-axis presents water levels (in blue) in the field water tube installed next to the sampling chamber used to measure the GHG emission rate for each treatment (BP and AP stand for baseline and alternative practices), and for the replicate chamber (R1, R2 and R3 denote three different replicates). When there was no water level data available for a given day, white gaps can be seen in the water level dataset. The sampling frequency for water level measurements in presented in Table S2. **(Red lines show N input)**

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19 *Supporting material for Kritee et al (2018): High nitrous oxide from rice cultivation*

20 *Supporting material for Kritee et al (2018): High nitrous oxide from rice cultivation*

21 *Supporting material for Kritee et al (2018): High nitrous oxide from rice cultivation*

22 *Supporting material for Kritee et al (2018): High nitrous oxide from rice cultivation*

Fig. S7 – Farm 4 (Controls)

24 *Supporting material for Kritee et al (2018): High nitrous oxide from rice cultivation*

Figs. S9-S14: Temporal variation in CH⁴ at all farms. The X-axis on these graphs indicate day after transplantation. The primary Y-axis presents GHG emissions in units of mg m⁻² h⁻¹ (in black closed circles). The secondary Y-axis presents water levels (in blue) in the field water tube installed next to the sampling chamber used for measuring GHG emission rate for each treatment (BP and AP stand for baseline and alternative practices), and the replicate chamber (R1, R2 and R3 denote three different replicates). When there was no water level data available for a given day, white gaps can be seen in the water level dataset. The sampling frequency for water level measurements in presented in Table S2.

See next seven pages.

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27 *Supporting material for Kritee et al (2018): High nitrous oxide from rice cultivation*

28 *Supporting material for Kritee et al (2018): High nitrous oxide from rice cultivation*

29 *Supporting material for Kritee et al (2018): High nitrous oxide from rice cultivation*

30 *Supporting material for Kritee et al (2018): High nitrous oxide from rice cultivation*

Fig. S13- Farm 4 (Controls)

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Fig. S15: Inverse relationship between N2O and CH⁴ emissions for average emissions from all thirteen treatments (6 seasons, two treatments and one control at Farm 4) Except during two seasons, one of the two GHGs (CH4 or N2O) was a dominant contributor to net GWP¹⁰⁰ (Figure 1). In two seasons (Farm 1 [2012] and Farm 3 [2012]), the contribution of CH⁴ and N2O fluxes to net GWP¹⁰⁰ was comparable possibly because the surface was sufficiently oxidized for N2O flux while the subsurface was simultaneously sufficiently reduced for significant CH⁴ flux[49](#page-85-7) . When average emissions from all thirteen treatments in this study are considered, there is an inverse exponential relationship between the two GHGs. Error bars represent 95% confidence intervals. High and medium water index farms (mild- or medium-intermittent flooding) show high variability in CH₄ but not much variation in N_2O . In *contrast, intense-intermittent farms show a relatively high range in N2O but not much variation in CH4.*

Fig. S16: Overall inverse relationship between N2O and CH⁴ emissions for individual replicates from each farm and treatment.

Figs. S17-S22: Correlation of N2O flux for all replicates for each treatment with water index (S17), inorganic N (S18), number of flooding events> 3 days (S19), added organic C (S20), added total N (S21) and Clay:Sand ratio (S22) When we consider the correlation of N2O emissions and individual parameters, N2O emissions were most strongly (and negatively) correlated with parameters that reflect extent of flooding at each farm (water index, maximum flooding duration, number of flooding events). See SI Table S34 for Pearson correlation coefficients between average N2O flux for each treatment and individual parameters.

Fig. S17 N₂O *vs.* Water index

Fig. S18 N₂O *vs.* Inorganic N (all replicates)

Fig. S19 N₂O *vs.* Number of Flooding events ($>$ 3 days)

Fig. S20 N₂O *vs.* organic matter

Fig. S21 N₂O *vs*. Total N (Inorganic N + minimum organic N)

Fig. S22 N2O *vs.* % Clay: % Sand in the soil

Fig S23 Number of Flooding events (> 3 days) vs water index (all replicates)

Fig. S24 Average N₂O *vs.* Average Inorganic N ($n = 13$ treatments with 3 replicates each)

Figs. S25-28: Correlation of average CH⁴ flux in each season with water index (S25), number of flooding events>3 days (S26), added organic C (S27) and SOC (S28) When we consider the correlation of CH⁴ emissions and individual parameters, CH⁴ emissions were most strongly (and positively) correlated with parameters that reflect extent of flooding at each farm (water index, maximum flooding duration, number of flooding events). See SI Table S36 for Pearson correlation coefficients between average CH⁴ flux for each treatment and individual parameters.

Fig. S25: CH⁴ *vs.* Water index

Fig. S26: CH₄ *vs.* number of flooding events ($>$ 3 days)

Fig. S27: CH⁴ *vs.* **added organic carbon** *The graph plots the maximum possible organic C input on the X-axis but the trend remains the same if the minimum possible organic C is plotted instead (see SI Table S32 for maximum and minimum possible organic C inputs). The points enclosed in red and blue circles correspond to two Farms with high water indices (mild-intermittent flooding).*

Fig. S28: CH⁴ *vs.* **soil organic matter (SOM)**

Fig. S29: Plot of fitted vs measured N2O emissions, using the multivariate regression model that includes water index, continuous flooding events and input of inorganic N. Notice the strong correlation between fitted and measured emissions ($R = 0.86$ *). The water index captures the cumulative flooding conditions at each Farm but the number of continuous flooding events reflects the temporal pattern that gave rise to the flooding conditions at a specific Farm. Water index, periods of continuous flooding and inorganic N explain 70%, 10% and 4% of the variance in the data, respectively. Even though periods of continuous flooding and inorganic N input explain a small fraction of the total variance when compared to water index, their addition to the model is statistically significant.*

Fig. S30: Plot of fitted vs measured CH⁴ emissions, using the multivariate regression model that includes continuous flooding events and soil organic carbon as parameters. Notice the strong correlation between fitted and measured emissions (R = 0.87). The number of flooding events and SOC explain 87% and 5% of the variance in the CH⁴ emissions, respectively.

Figs. S31-33 and S34-35: We compared the two treatments (AP vs BP) from each farm to demonstrate how specific changes in important parameters trigger or suppress N2O and/or CH⁴ emissions. These examples cannot yet be generalized; however, they illustrate the potential effect of managing certain parameters. To visualize this analysis we use parallel coordinate plots[50](#page-85-0). With these plots, we can visualize how a set of parameters change among a pair of treatments. Each parallel Y-axis represents the range of one specific parameter. Solid horizontal lines connect the values between parameters for each Farm. SI Figures S31-33 and S34-35 show N2O and CH⁴ emissions as well as parameters that had the most statistically significant relationships with rice GHG emissions with respect to flooding characteristics, soil characteristics, and inputs: water index, continuous flooding events, inorganic N input, organic C input, soil organic carbon (SOC) and clay/sand ratio.

Please see farms showing N2O dominance in SI Figure S31-33 and farms showing dominance of CH⁴ in SI Figure S34-35.

Fig. S31: Parallel coordinate plot for Farm1-2012-AP (lighter blue) and Farm1-2012-BP (darker blue). The light grey lines in the background show treatments not considered in this analysis. This figure compares Farm 1 (2012) AP and BP treatments. BP treatments had higher N2O emissions (AP $=$ 3.0 kg N₂O ha⁻¹, BP = 8.3 kg N₂O ha⁻¹). We see the inverse relationship with CH₄ emissions, where *AP had slightly higher emissions (AP = 81.1 kg CH₄ ha⁻¹, BP = 66.5 kg CH₄ ha⁻¹). These Farms had similar flooding characteristics: both had comparable water index values (close to the median of all the Farms) and the same number of continuous flooding events. One of the main differences is the inorganic N input (AP = 0 kg N ha⁻¹, BP = 91 kg N ha⁻¹). As shown in Equation 1, a higher inorganic N input is related to higher N2O emissions. This example also shows a positive correlation between clay/sand ratio and N2O emissions. BP had a 50% higher clay/sand ratio (AP = 0.18, BP = 0.27) and even though this soil characteristic parameter did not show up in the multivariate regression model (Equation 1), this example qualitatively shows difference in clay/sand ratio between BP and AP as a potential cause of difference in N2O emissions under similar flooding characteristics.*

*Fig. S32: Parallel coordinate plot for Farm3-2012-AP (lighter blue) and Farm3-2012-BP (darker blue). The light grey lines in the background show treatments not considered in this analysis. This figure compares Farm 3 (2012) AP and BP treatments. BP treatments had significantly higher average N*₂*O emissions (14.5 kg N*₂*O* ha⁻¹; maximum N₂*O emissions among all 13 treatments) and very similar CH⁴ emissions. These sites had similar water indices (close to the median of all sites) and similar continuous flooding events (minimum from all sites). For both sites, inorganic N input is above 100 kg ha-1 , however, site BP had almost twice the inorganic N input and higher N2O emissions than AP. As with Farm 1, similar flooding characteristics and changes in the inorganic nitrogen input affect N2O emissions without having a significant effect on CH⁴ emissions.*

Fig. S33: Parallel coordinate plot for Farm3-2013-AP (lighter blue) and Farm3-2013-BP (darker blue). The light grey lines in the background show treatments not considered in this analysis. This figure compares AP and BP treatments at Farm 3 (2013). In this case, BP treatment had higher N2O emissions (AP = 7.3 kg N₂O ha⁻¹, BP = 11. kg N₂O ha⁻¹) and similar CH₄ emissions. BP had a lower water index, higher inorganic N input and higher clay to sand ratio. The difference in water index $AP = -858$ *vs BP = -1,036) was the main driver of N₂O emissions.*

Fig. S34: Parallel coordinate plot for Farm4-2014-AP (lighter blue) and Farm4-2014-BP (darker blue). The light grey lines in the background show treatments not considered in this analysis. This figure compares Farm 4 AP and BP treatments. N2O emissions for these two treatments are close to the lower end of all treatments, although slightly higher for BP treatments (AP = 0 kg N_2O *ha⁻¹, BP =* 0.57 kg N₂O ha⁻¹). CH₄ emissions are slightly higher for Farm AP (AP = 154 kg CH₄ ha⁻¹, BP = 141 *kg CH⁴ ha-1). High water index and an elevated number of continuous flooding events suppress N2O emissions for both AP and BP. Conversely, these high flooding conditions trigger CH⁴ emissions and in particular the relatively higher number of continuous flooding events in AP corresponds to the higher CH⁴ emissions at that farm.*

Fig. S35: Parallel coordinate plot for Farm 5-2013-BP (darker blue) and Farm 5-2013-AP (lighter blue). The light grey lines in the background show treatments not considered in this analysis. This figure compares Farm 5 AP and BP treatments. In this case, both AP and BP had similar and low N2O emissions. However, both treatments had significantly high CH4 emissions (where AP = 216 kg CH_4 *ha*⁻¹, $BP = 286$ kg CH_4 *ha*⁻¹), the maximum measured in this study. These two treatments had *similar inputs and soil characteristics (clay/sand ratio), but different flooding characteristics with overall high water index values. The soil organic C from both AP and BP treatments are at the maximum observed in this study, and as shown in Equation 2, this high soil organic C content supports the high CH⁴ emissions.*

Fig. S36: Indian subcontinent rice management classes The spatial layout of water management classes for rice farms in the Indian subcontinent (Image from Gumma et al. 2011)[51](#page-85-1) .

Figure S37: Relationship between rice area under irrigation vs. potential for high N2O emissions. If different states move from medium to intense intermittent flooding (or from minimum water index and maximum flooding events to minimum water index and minimum flooding events scenarios), the net susceptibility of different states in India to increased N2O emissions as calculated by Equation 1 (See SI Table S42) will depend on the percentage of area under irrigation[51](#page-85-1) . States in India that have higher percentage rice under irrigation (e.g., Delhi, Punjab or Karnataka are more susceptible to high N2O emissions under reduced flooding (i.e., intense intermittent flooding) simply because higher area under irrigation implies that with reduced flooding more total rice area will have lower water indices and hence higher N2O emissions based on Equation 1 (SI Table S42). Irrigated area for each state was estimated by aggregating results from all twelve categories (SI Table S38) and classifying each pixel from the Gumma et al. (2011) dataset as irrigated or non-irrigated pixel.

Fig. S38 Reduction in climate impacts vs reduction in yields Comparison of alternate treatments with corresponding baseline treatments at five farms. There is no direct correlation between reduction in yields and reduction in climate impacts which implies that we should be able to optimize management practices such that yields are maximized but climate impacts are minimized.

Supporting Tables

(All supporting tables are available as Dataset S1)

Supporting Table S1 Indian studies

(Too large to be pasted as an image, available only as an Excel spreadsheet, includes 39 studies on rice GHG emissions from India)

** Lower seedling age was recommended by local experts ** Lower seedling age was recommended by local experts

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¹ DAT Days after transplantation

2 For baseline seed rate survey results see SI Table S10 To have uniform seed rate across all treatments, a seed rate of 61kg/ha, which is within the range seen in baseline surveys, was used.

3 For close survey based FYM results, supporting Table S11. Total % O.C assumed ranged from 18 to 22% (Tennakoon & Hemamala-Bandara,

4 *Gliricidia Sp* . For baseline survey results, see Table S11. Higher rate was applied to have uniform application across all treatments. Total %C was assumed to range from 21 to 23 (Tennakoon and Hemamala-Bandara, 2003).

⁵ For matching survey results see SI Table S11

6 Mixture of 200kg dry cowdung, 10L cow urine, 2kg jaggery,2kg pulse powder, handful of anthill soil after being left in a cool dry place for 7 days. Total N% of GJWM assumed to be 0.75% (Kritee et.al.2015). Because dung was the major ingredient, total %C assumed ranged from 18

 7 Organic C content of neem cake was assumed to be between 25 to 50%.

8 Local liquid biofertilizer. 10kg cowdung, 10L cow urine, 2kg jaggery,2kg pulse powder, handful of anthill soil in 200L water, mixed regularly for 2 days. Total N% of Jeewamrutha assumed to be 0.2% (Kritee et.al. 2015).

⁹ For total organic N calculations, refer to SI Table S24

 1 DAT Days after transplantation

2 For baseline seed rate survey results see SI Table S12. To have uniform seed rate across all treatments, a seed rate of 61kg/ha, which is within the range seen in baseline surveys, was used.

 3 For baseline survey results see SI Table S13. A higher rate of FYM was added across all treatments as recommended by local experts because this farm was a new rice plot which had been left fallow for several years. See SI Table 2.1 for %C content.

4 For baseline survey results, see SI Tables S3 and S13. Because this was a new rice plot, inorganic N added to this farm was equal to the average amount used by the top 10% highest inorganic N using farmers in the survey.

⁵ For matching survey results see SI Table S13

6 Mixture of 200kg dry cowdung, 10L cow urine, 2kg jaggery,2kg pulse powder, handful of anthill soil after being left in a cool dry place for 7 days. %C and %N were assumed to be similar to FYM. See SI Table S25.

7 Local liquid biofertilizer. 10kg cowdung, 10L cow urine, 2kg jaggery,2kg pulse powder, handful of anthill soil in 200L water, mixed regularly for 2 days. Total N% of Jeewamrutha assumed to be 0.2% (Kritee et.al. 2015)

 8 The range of %C in sheep manure was assumed to vary from 30 to 40% (Gibert et al, 2004)

⁹ For total organic N calculations, refer to SI Table S25

¹ DAT Days after transplantation

² For matching survey seed rate, see SI Table S14. Because of large difference between survey results for seed rate and AP seed rate recommended by local stakeholders. Seed rates were kept different for AP and BP treatment

 3 Since FYM application was not a mainstream practice as evident from the surveys, BP plots were not treated with FYM. For AP plot, total N% in FYM was assumed to be 0.5%. Total % O.C assumed ranged from 18 to 22% (Tennakoon and Hemamala-Bandara, 2003).

4 See matching survey results in SI Table S15. MoP stands for Muriate of Potash and SSP stands for Single Superphosphate.

⁵ See SI Table S26

 6 Total % N in neem cake is assumed to be 5 and C% varies between 25 and 50.

 7 For total organic N calculations, refer to SI Table S26

* For actual application dates, refer to SI Fig. S5.

¹ DAT Days after transplantation

² For matching survey seed rate, see SI Table S16. Because of large difference between survey results for seed rate and AP seed rate recommended by local stakeholders. Seed rates were kept different for AP and BP treatment. For BP, seed rate which is within the range of survey results were used.

³ FYM was added by 71% farmers as per 2013 surveys, see SI Table S17.

⁴ See matching survey results in SI Table S18. Complex 17:17:17.

5 Enriched FYM has 500kg FYM, 1kg Pseudomonas, 1kg Phospho bacteria, 1 kg *Trichoderma viride* , 1 kg *Metarhizium Sp.* , 250ml *Verticelium lecanni*, 250ml *Azospirillum*, 250ml Potash mobilizer, 1litre sea weed, 200ml Humic acid, 1litre green growth and 200 litres Amudhakaraisal. Because of small quantities of other mostly liquid ingredients, total N% and C% of enriched FYM was assumed to be similar to FYM.

6 Local liquid biofertilizers. Amudha Karaisal is mixture of 1 kg of fresh cow dung, urine and Ipomoea Cornea leaves each and 25 gm of jaggery in 10 litres of water which is stirred (3X/day) and used after 24 hrs by diluting in 10 L water. Green Growth is 1:20 dilution of 1 kg of jaggery is dissolved in 20 L of water and 1 L of "mother culture". Themore karaisal is a mixture of 6 grated coconut, 2 L of butter milk, 0.5 kg jaggery, 10 bananas incubated for 15 days and spraye at 1: 20 ratio (Chandra, 2005),

⁸ Total %C in groundnut and neem cake is assumed to be between 25 and 50% (Chong, 2005).

⁹ For total organic N calculations, refer to SI Table S27

* For actual application dates, refer to SI Fig. S6

 1 DAT Days after transplantation

² 44% of survey respondents used FYM, see SI Table S20 for matching input quantity.

³ For matching survey results, see SI Table S21

4 Enriched FYM has 500kg FYM, 1kg Pseudomonas, 1kg Phospho bacteria, 1 kg *Trichoderma viride* , 1 kg *Metarhizium Sp.* , 250ml *Verticelium lecanni*, 250ml *Azospirillum*, 250ml Potash mobilizer, 1litre sea weed, 200ml Humic acid, 1litre green growth and 200 litres *Amudhakaraisal.* Because of small quantities of other mostly liquid ingredients, total N% and C% of enriched FYM was assumed to be similar to FYM.

⁵ For survey results see SI Table S21. BP inputs were slightly higher than average but within the range found in the survey results.

 6 Total %C in neem cake is assumed to vary between 25 and 50% (Chong, 2005)

 7 For total organic N calculations, refer to SI Table S28

¹ DAT Days after transplantation

 2 For baseline seed rate survey results see SI Table S22. Because of large difference between survey seed rate and AP treatment seed rate as suggested by local stakeholders. Seed rates were kept different for AP and BP treatment. For BP, seed rate which is within the range of survey results were used.

 3 For survey results see SI Table S23. Comples 17:17:17 was applied at a slightly lower rate within the range of survey results

 4 Total %C in neem cake is assumed to be between 25 and 50%.

⁵ For matching survey results, see SI Table S23

6 In times of cold weather, Urea uncubated overnight with moist soil helps to release N quickly during panicle initiation stage and protects rice plant from yield loss.

 7 For survey results see SI Table S23. As compared to surveys, a slightly higher rate that was within 1 SD of the average was applied.

8 For total organic N calculations, refer to SI Table S29

SI Table S10 Farm 1: Seed rate survey results

Table S11 Farm 1: Organic & Inorganic fertilizer use survey results

SI Table S12 Farm 2: Seed rate survey results

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SI Table S13 Farm 2: Organic & Inorganic fertilizer use survey results L

SI Table S14 Farm 3 (2012): Seed rate survey results

SI Table S15 Farm 3 (2012): Organic & Inorganic fertilizer use survey results

SI Table S16 Farm 3 (2013): Seed rate survey results

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SI Table S17 Farm 3 (2013): Organic fertilizer use survey results

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SI Table S18 Farm 3 (2013): Inorganic fertilizer use survey results

SI Table S19 Farm 4: Seed rate survey results

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SI Table S20 Farm 4 Organic fertilizer use survey results

SI Table S21 Farm 4 Inorganic fertilizer use survey results

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SI Table S22 Farm 5 Seed rate survey results

SI Table S23 Farm 5: Inorganic fertilizer use by BP farmers based on survey

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Table S24 Cumulative mineralized N input during the cropping season at Farm 1 (2012) **Table S24 Cumulative mineralized N input during the cropping season at Farm 1 (2012)**

Table S25 Cumulative mineralized N input during the cropping season at Farm 2 (2013) **Table S25 Cumulative mineralized N input during the cropping season at Farm 2 (2013)**

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Table S26 Cumulative mineralized N input during the cropping season at Farm 3 (2012) **Table S26 Cumulative mineralized N input during the cropping season at Farm 3 (2012)** *Heterosporous free-floating freshwater ferns that live symbiotically with Anabaena azollae, a nitrogen-fixing blue-green algae. The estimates of N fixed by azolla can fix vary from 53 to *Heterosporous free-floating freshwater ferns that live symbiotically with Anabaena azollae, a nitrogen-fixing blue-green algae. The estimates of N fixed by azolla can fix vary from 53 to 1000 kg/ha N, with dry matter production between 39 and 390 tons/ha, in crop cycles of 40-365 days {FAO, 2009 #357}. At Farm 3, Azolla dried up ~30 days after inoculation and we 1000 kg/ha N, with dry matter production between 39 and 390 tons/ha, in crop cycles of 40–365 days {FAO, 2009 #357}. At Farm 3, Azolla dried up ~30 days after inoculation and we assume that a total of 50 Kg N/ha was fixed in azolla which matches the estimates used earlier {Akiyama, 2005 #190}. Using a C:N ratio of 10 {Ferentinos, 2002 #356}, the minimum assume that a total of 50 Kg N/ha was fixed in azolla which matches the estimates used earlier {Akiyama, 2005 #190}. Using a C:N ratio of 10 {Ferentinos, 2002 #356}, the minimum organic C from azolla was estimated to be 500 and based on the range of dry matter production{Ferentinos, 2002 #356}, the maximum estimate was placed at 1000 Kg C/ha. organic C from azolla was estimated to be 500 and based on the range of dry matter production{Ferentinos, 2002 #356}, the maximum estimate was placed at 1000 Kg C/ha.

Table S27 Cumulative mineralized N input during the cropping season at Farm 3 (2013) **Table S27 Cumulative mineralized N input during the cropping season at Farm 3 (2013)**

*Total % N in Groundnut cake assumed to be 7 (Average of Chong, 2005)

*Total % N in Groundnut cake assumed to be 7 (Average of Chong, 2005)

** See SI Table 4.3

** See SI Table 4.3

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 $\overline{\mathbf{r}}$ $\overline{}$ $\overline{}$ ### Set 3 corresponds to mineralization of 45, 20,10% of the total N in 1st, 2nd and 3rd year after application of organic matter

Table 579 Cumulative mineralized N innut during the cronning season at Farm 5 (2013) **Table S29 Cumulative mineralized N input during the cropping season at Farm 5 (2013)**

Fach-Vinglies one evidence of drainage related N2O flux for the the topical creates the state is the beamed be whole beamed by the context of the state of the state of the state of the ding. Finance is find the state of fl

wel below

7.5 cm. When

water level was below 0 cm after at least 4 days of flooding.

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he color of V is red, drainage implies that the

Table S30: Evidence of variation in nitrous oxide flux due to inorganic or organic N inputs and drainage events

73 *Supporting material for Kritee et al (2018): High nitrous oxide from rice cultivation*

Table S31: Evidence of variation in methane flux due to drainage events and growth stages **Table S31: Evidence of variation in methane flux due to drainage events and growth stages**

4 days of flooding.

Supporting material for Kritee et al (2018): High nitrous oxide from rice cultivation

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Supporting material for Kritee et al (2018): High nitrous oxide from rice cultivation

** Neglecting negative nitrous oxide emissions. Values used in Figure 3*

Table S43: Example of effect of sampling frequency on N2O and CH⁴ emissions

Reduction in sampling frequency results in much larger error in estimation of N₂O fluxes than CH4, especially for BP treatments which have high inorganic N input and N₂O fluxes are higher than 0.25 tCO2e100/ha. Exact extent of the effect of sampling frequency on seasonal flux will vary from case to case (see Tiwari et al (2015) for details). In all cases, inability to capture just a few (e.g., 4-6) highest fluxes can result in a very high extent of underestimation of seasonal N₂O fluxes (Figures S3-S8).

Table S44 Summary of change in understanding of climate impacts of rice cultivation

* Our emission factor estimates include both inorganic N mineralized organic N in its calculation. If we didn't include organic N, emission factors would be higher. We didn't have N = 0 controls at all sites. [#] Based on 2007 IPCC report which doesn't give mitigation estimate for rice nitrous oxide but a range for general crop N_2O mitigation potential.

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