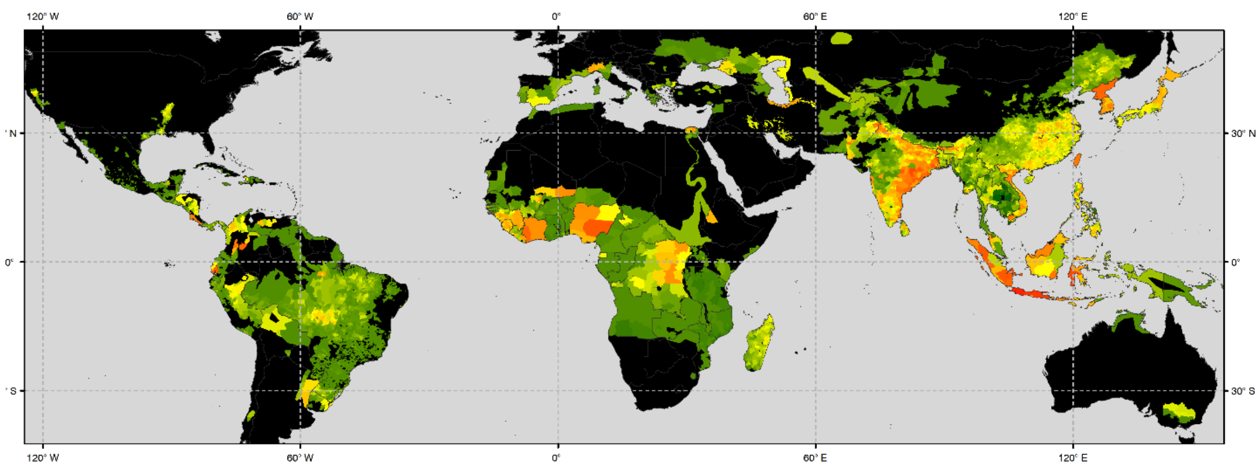
Global risk assessment of high nitrous oxide emissions from rice production

Incorporating the discovery of high N2O fluxes under intermittent flooding



A white paper by Environmental Defense Fund and partners

Released on September 10, 2018

Environmental Defense Fund

Environmental Defense Fund is dedicated to protecting the environmental rights of all people, including the right to clean air, clean water, healthy food and flourishing ecosystems. Guided by science, we work to create practical solutions that win lasting political, economic and social support because they are nonpartisan, cost-effective and fair.

257 Park Avenue South
New York, NY 10010
Telephone: 212 505 2100
Fax: 212 505 2375
edf.org

Authors

This white paper was authored by K. Kritee*, Jeremy Proville*, Daniel Zavala-Araiza, Joseph Rudek, Richie Ahuja, Steven Hamburg from Environmental Defense Fund and our scientific partners Tapan Adhya, Terrance Loecke and Drishya Nair.

*Equal contributors

Acknowledgments

The authors thank, without implicating, the entire Fair Climate Network team for their collaboration, ideas on experimental design and help in conducting the experiments whose results are the basis of this white paper. Any errors are our own. We also acknowledge Tashina Esteves and Rakesh Tiwari for a few diagrams and photographs. This scientific dimension of these low-carbon (climate smart) farming initiatives in India was embedded in our over-arching low-carbon rural development strategy; and this white paper complements the results that will soon be published in a peer-reviewed scientific journal.

Executive Summary

Rice provides livelihood to ~150 million households, is a staple for half of humanity and uses 11% of arable land and a third of irrigation water. Continuously flooded rice farms function like wetlands and produce ~12% of total anthropogenic emissions of methane (CH_4), a short-lived greenhouse gas (GHG). Currently, CH_4 from global rice farms accounts for ~50% of all crop related GHG emissions and rice has the highest climate impact of any crop per unit calorie. Based on an as of yet unverified assumption that almost all irrigated rice fields are continuously flooded and that >90% of the climate impact of rice production results from CH_4 emissions, the global climate mitigation community has focused heavily on water management of rice (i.e., intermittent flooding) to reduce CH_4. These efforts had until recently ignored the potential of large adverse impacts of intermittent flooding regimes on emissions of nitrous oxide (N_2O), a long-lived GHG.

A recent peer-reviewed study by Environmental Defense Fund (EDF) and partners showed that N_2O emissions per unit area could be three times higher than ever reported before and that these emissions increase inversely with the degree of flooding. This study also suggested that intermittent flooding at rice farms is likely much more common (especially in South-Asia, Africa and South America) than acknowledged in existing studies and/or in UNFCCC reports. In other words, N_2O emissions from rice cultivation could be much higher than previously reported, with the net effect of increasing both the short- and the long-term climate impacts of rice production. These N_2O emissions could also increase very significantly as a result of efforts to mitigate CH_4 emissions through intermittent flooding. An extrapolation of experimental findings to Indian subcontinent has already suggested that under intensely-intermittent flooding scenarios, Indian rice farms can produce 530,000-790,000 tons N_2O year^{-1} which is 30-45 times higher than emissions under continuous flooding. This peer-reviewed EDF study showed that high N_2O emissions can be reduced through shallow (mild-intermittent) flooding along with co-management of fertilizers resulting in reduced net climate impacts of rice cultivation in both the long and the short term. The potential global implications of the discovery of high N_2O fluxes need to be assessed given the rapid uptake of intermittent flooding based CH_4 mitigation strategies.

In this white paper, within the limitations of currently available data, we quantify the potential global risk of a large climate impact due to N_2O emissions from rice paddies globally through a geospatial extrapolation. We limit our interpretation to caution (but not claim) that N_2O emissions from global rice cultivation could be very high and inadvertently increased through current climate mitigation policies and practices being implemented for this sector. The scale of this N_2O problem could be large (450 – 700 MMT CO_2e_{100}), equivalent to annual CO_2 emissions from 200 coal power plants, potentially making the net climate impact from global rice cultivation as high as 1930 MMT CO_2e_{100}. If future research upholds the findings of this white paper, the climate impact of N_2O from global rice cultivation could be tens of times larger than previous estimates for continuous flooding scenario. Given the limited availability of high resolution global flooding regime maps and N_2O data from a range of intermittently flooded rice farms from various geographies, we strongly encourage the scientific and policy community to undertake further research to ensure that long-term perverse outcomes of CH_4 mitigation efforts do not undercut their value.

Introduction

Rice is a critical global cereal. Currently, methane (CH_4) emissions from global rice cultivation (here-after rice-CH_4) accounts for ~50% of all crop related GHG emissions and rice has the highest climate impact of any crop per unit calorie generated. Continuously flooded rice fields function like wetlands and are known to produce ~12% of total anthropogenic CH_4 emissions. Rice-CH_4 is currently estimated to contribute ~0.1 Wm^{-2} to the radiative forcing (Ciais et al., 2014; Kirschke et al., 2013; Turner et al., 2016). Nitrous oxide, (N_2O) traps more heat over all timeframes as compared with CH_4 on a weight basis ($GWP_{100\text{-years}}$ of 298 *vs* 34; $GWP_{20\text{-years}}$ of 268 *vs* 86) (Myhre et al., 2013), and it has a longer atmospheric lifetime (121 *vs* 12 years) (Myhre et al., 2013). While recent scientific research recognizes N_2O emissions from rice farms (here-after rice-N_2O) need to be addressed (Carlson et al., 2017; Lagomarsino, 2016; Li et al., 2011; Linquist et al., 2012; Smith et al., 2007), guidelines for reducing climate impacts of rice continue to assume that rice-N_2O is negligible or small at <10% of the total $CO_2e_{100\text{-years}}$ even under intermittently flooded conditions (CCAC, 2014; CCAFS, 2017; Richards and Ole-Sander, 2014). None of the major rice-producing countries report rice-N_2O in their national GHG inventories submitted to the United Nations (Smith et al., 2007). Crucially, most policy recommendations on rice management that include consideration of climate impacts focus on reducing rice-CH_4 by alternate wetting and drying (AWD), also called intermittent flooding. Water levels during intermittent flooding are typically allowed to fall to 15 cm below the soil surface before another round of irrigation (CCAC, 2014; CCAFS, 2017; Richards and Ole-Sander, 2014).

Despite being one of the few crops whose climate impacts have been studied over two decades, the potential of high N_2O emissions from rice cultivation from non-continuously flooded rice farms had been under appreciated. This is because most research done to capture rice-N_2O to date has been performed at farms with continuous or mild-intermittent flooding under the assumption that these flooding regimes are representative of most rice cultivation, given their weed and pest control benefits (GRiSP, 2013). Under continuous flooding, redox conditions are conducive for methanogenesis, but not ideal for formation of N_2O. Mid-season drainage (a form of mild-intermittent flooding that causes a single long aeration event) brings redox conditions to levels that limit methanogenesis but are still lower than suitable for large amounts of N_2O formation (Hou et al., 2000; Johnson-Beebout et al., 2009). However, more intense forms of intermittent flooding cause multiple drying and wetting events and increase the potential for high N_2O emissions. Such multiple aeration events are common at both irrigated and rainfed rice farms in many parts of the world as a result of temperature/rainfall regimes, unreliable water/electricity supply, soil quality, and topography (Alam et al., 2011; Erenstein, 2009; Hobbs, 1996; Pereira et al., 2000; Suryavanshi et al., 2013). And yet, until recently, no studies had examined rice farms with intensely intermittent flooding. In addition, very few studies have been conducted at other forms of intermittent flooding (including mid-season drainage) at a sampling intensity sufficient to accurately capture the high temporal variability in N_2O fluxes.

During 2012-2014, a coalition of Environmental Defense Fund and Fair Climate Network researchers measured GHG emissions at five farmer-managed rice farms that are conventional under non-continuous flooding regimes across three agro-ecological regions in south India (Kritee et al., 2018). The goal was to compare climate impacts of rice cultivation from "baseline" practices (conventional practices identified via farmer surveys) to a series of farm-specific "alternate" practices. Using GHG emission datasets from intermittently flooded rice farms (with varying degrees of flooding), this study found that N_2O seasonal emissions per unit area can be three times higher than previously reported (Kritee et al., 2018). To be specific, the highest seasonal and hourly N_2O fluxes measured in this study (Kritee et al., 2018) were 33 N_2O kg ha^{-1} $season^{-1}$ and 15,000 µg N_2O m^{-2} h^{-1}, respectively. The previously reported maximum rice-N_2O fluxes (9.9 kg N_2O ha^{-1} $season^{-1}$ and 2100 µg m^{-2} $hour^{-1}$) were from a farm in Italy which used mild intermittent flooding.

In addition to greenhouse gas (GHG) emission measurements, a total of 25 management parameters were tested in this study for potential correlations with rice-N_2O and rice-CH_4 (Kritee et al., 2018). These parameters included seasonal temperature characteristics, several water management related variables, crop organic and inorganic inputs, soil characteristics including organic carbon (SOC) content and texture as well as pH and electrical conductivity (EC).

The following empirical (multiple regression) model best described the N_2O emissions from rice farms (p-value <0.001, adjusted $R^2 = 0.80$):

$$\mathbf{N_2O = -0.01*(water\ index) - 0.91*(flood\ events_{>3\ days}) + 0.02*N_{inorganic} + \epsilon_1} \qquad \textbf{(Equation 1)}$$

where N_2O represented emissions in kg-N ha^{-1} $season^{-1}$, flood $events_{>3\ days}$ was the number of times a plot had flooding (>0 cm water level) for more than3 days, $N_{inorganic}$ was inorganic nitrogen (N) input in kg ha^{-1} and ϵ_1 is statistical error. Water index, a measure of cumulative extent of flooding, was seen as a proxy for soil redox conditions, emerged as the most important predictor of N_2O and is measured by observing water levels in a field water tube every day. For a given water index, flood $events_{>3\ days}$ described the number of multiple aeration events. When longer (>3 day) flood events predominated, shorter flood events (and hence multiple aeration) events were less frequent, resulting in lower rice-N_2O. This model conveys that reduction in flooding (via a reduction in water index or number of flooding events) oxygenates the soil, raises soil redox and enhances microbial processes that convert inorganic nitrogen lead into larger amounts of N_2O.

This study also investigated potential risk of high rice-N_2O on the Indian subcontinent by extrapolating the above empirical model (Equation 1) under three hypothetical flooding scenarios (continuous, medium- and intense-intermittent flooding for irrigated farms, see Table 1 for description of different flooding regimes) (Kritee et al., 2018). Please see notes on different types of models in Appendix 1. This extrapolation to Indian subcontinent suggested that under medium- or intense-intermittent flooding, Indian rice farms can produce 530,000-790,000 tons N_2O $year^{-1}$

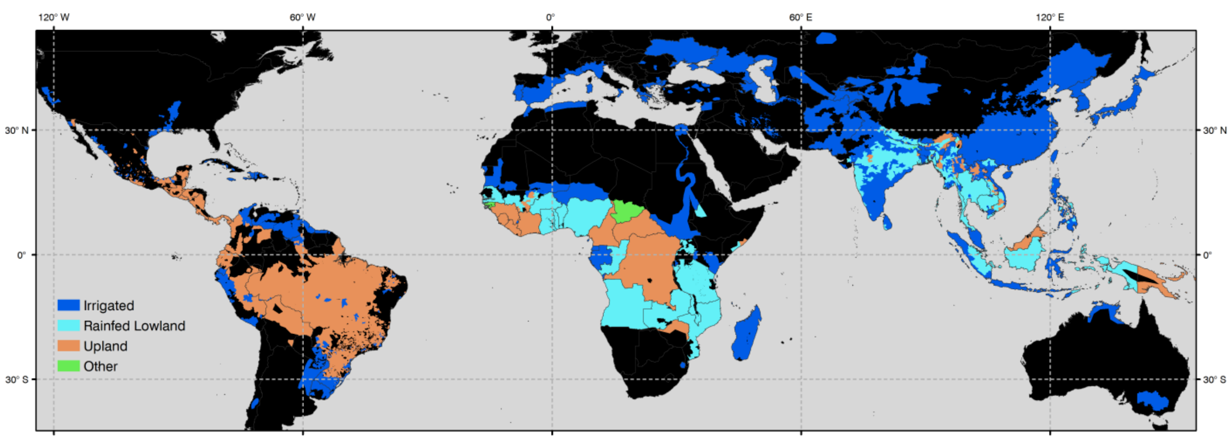
which was 2-3 times higher than emissions under mild-intermittent flooding (EPA, 2013) and 30-45 times higher than emissions under continuous flooding scenarios(Gerber et al., 2016).

In contrast to rice-N_2O, rice-CH_4 was found to be positively correlated with parameters that reflect flooding extent and amount of soil organic matter, consistent with past findings that the lowest CH_4 fluxes are recorded on farms with multiple aeration events and poor soils (Sass, 2003). The following multiple regression model best explained seasonal rice-CH_4 data (p-value <0.001, adjusted $R^2 = 0.91$) (Kritee et al., 2018).

$CH_4 = 34*(\text{flood events}_{>3\ \text{days}}) + 88*SOM + \epsilon_2$ (Equation 2)

In this equation, CH_4 represented emissions in kg CH_4 ha^{-1} $season^{-1}$, flood events$_{>3\ \text{days}}$ was the number of times a plot had flooding (>0 cm water levels) for more than three days, SOM was soil organic matter in % and ϵ_2 is statistical error.

Figure 1: Global rice management classes*. This map depicts the most dominant management class of the four management classes (irrigated, rainfed lowland, rainfed upland and other) for each rice growing region by defined by IRRI (2011). Dominance here is defined as the management class which had the largest percentage of rice area for each region but there may be regions where all four classes coexist.*



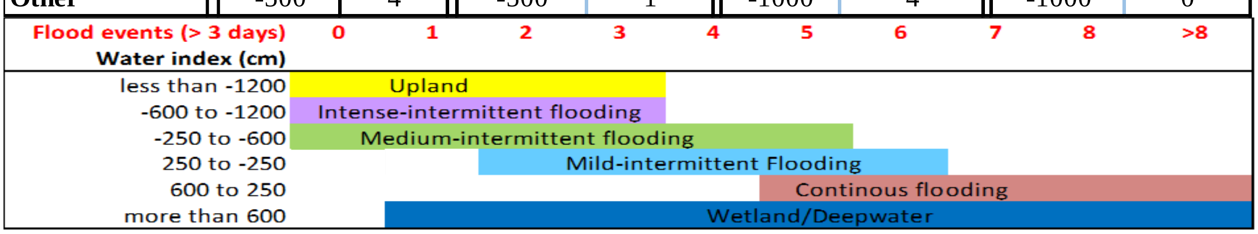
High nitrous oxide emissions are likely to be a persistent problem across many non-continuously flooded rice-producing regions worldwide – not simply an issue pertaining to India or the Indian Subcontinent. The global agro-ecological community must proceed with care and look towards co-managing CH_4 and N_2O in rice farms, to mitigate both the long term and the short term climate pollution. This white paper builds upon the findings reported in our peer-reviewed research article (Kritee et al., 2018) and provides a global extrapolation of the experimental findings from Indian subcontinent. While extrapolation of region-specific findings to additional agro-ecological regions should be done cautiously (see 'limitations' in Appendix 2), such an analysis is critical in order to characterize the scale of global risks of high N_2O emissions. This extrapolation is especially important because intermittent flooding is being actively promoted to reduce methane (CH_4) from rice through policy frameworks at national and international levels (CCAC, 2014; CCAFS, 2017; Richards and Ole-Sander, 2014). As such, the implications of our data on the potential magnitude of global rice-N_2O need to be considered.

Methods

To begin the process of estimating N_2O fluxes for a given area of rice cropland, we assembled a series of input datasets for each independent variable in Equation 1. The first two of these, water index and number of flood events, are largely governed by the land/terrain type and the irrigation management at a given location. For the purposes of our extrapolation, we determined the likely range for each variable under the four different rice classifications given in the global dataset compiled by International Rice Research Institute (IRRI) (IRRI, 2011) where the four global rice management classes were available at 1.2 arc-minute (~2.2 km) (IRRI, 2011) grid cell resolution. This IRRI database has been updated relative to an earlier global study that modeled climate impacts of rice cultivation and assumed that 90% of global area under rice cultivation has a continuous flooding regime (Gerber et al., 2016). Figure 1 above illustrates only the predominant rice category for each region, however the actual dataset provides a detailed breakdown of rice area into four categories for each location (in hectares). Rice-N_2O emissions were calculated for each of the four classes individually, by region, and then recombined to generate a total estimate on the basis of the weighted distribution of all four classes.

Table 1 *Details of the assumed ranges for water index and number of flooding events that are more than 3 days in length by management class.*

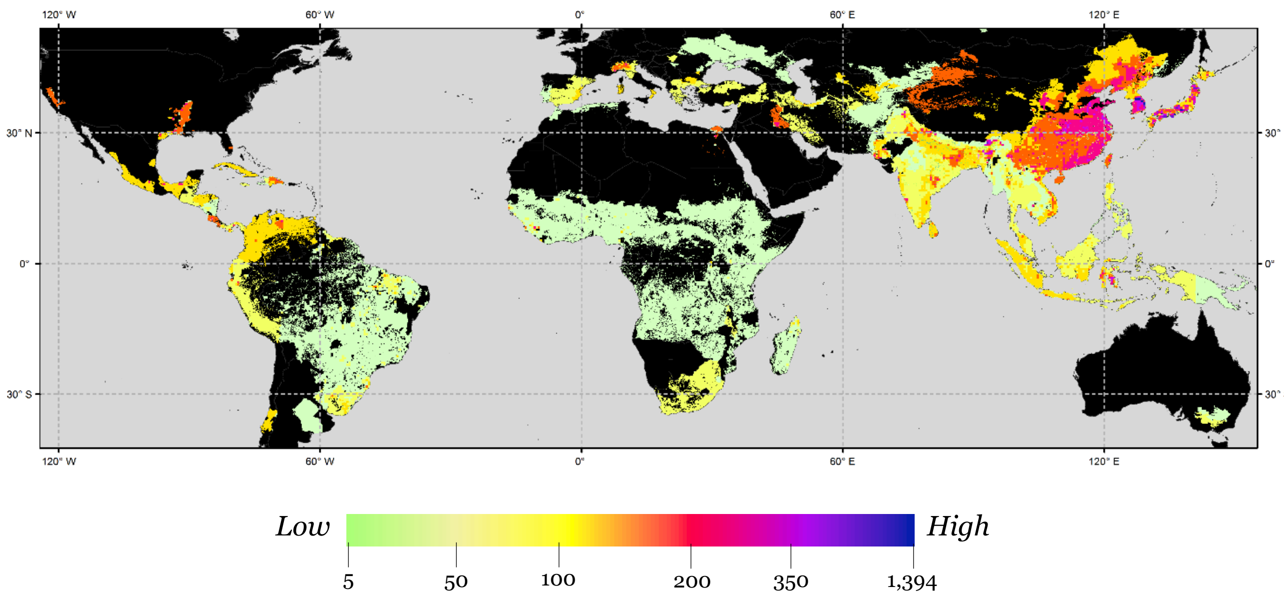
Assumed water Index & number of flooding events for different rice water management classes								
	Continous flooding scenario		**Mild Intermittent flooding scenario**		**Medium Intermittent flooding scenario**		**Intense Intermittent flooding scenario**	
	Water index	**Flood events**	**Water index**	**Flood events**	**Water index**	**Flood events**	**Water index**	**Flood events**
Irrigated	400	8	-200	1	-1100	8	-1100	1
Rainfed lowland	500	1	200	1	200	1	200	1
Upland	-1500	2	-1500	1	-2000	2	-2000	0
Other	-500	4	-500	1	-1000	4	-1000	0



A dataset to provide a spatially explicit measure of inorganic N inputs was taken from Mueller (Mueller et al., 2012). This is the most recent and highest resolution global fertilizer use dataset available specific to rice (see Figure 2). The N fertilizer dataset was available at 5 arc-minute (~10 km) (Mueller et al., 2012) grid cell resolution. It should be noted that N rates may have increased (or in some cases decreased) since the year 2000 when their dataset was collected (see limitations in Appendix 2).

Input datasets were converted to a common 1.2x1.2 arc-minute raster format, and N_2O emission rates were then estimated using Equation 1. Regional statistics were summed to form national totals, and converted into units of MMt-N_2O emissions.

Figure 2: Global rice inorganic N fertilizer use *Values are in kg ha^{-1} and averaged for the year 2000, spanning from 5 to 1,394 with a mean of 86. (Mueller et al., 2012)**.** In Kritee et al (2018), values ranged from 0 to 243.*



Results

Scale of Global Risk of N_2O from Rice Production

Our global risk assessment of rice-N_2O (Tables 2-3) based on the extrapolation of regression coefficients in Equation 1 to all the rice growing regions in the world (Figure 3) is based on the four global rice water management regimes (IRRI, 2011) and region specific N fertilizer application rates (Mueller et al., 2012).

Panels 3A-C and 3D-F are presented in sets of three scenarios, with associated assumptions as laid out in Figure 1 and Table 1. Panels 3A-C illustrate rice-N_2O risk per unit area (See Table 2). Panels 3D-F show total N_2O risk for a region after accounting for the net harvested area of rice in that region in order to provide a metric more reflective of risk associated with absolute levels of N_2O emissions (see Table 3).

In general, areas with conditions leading to greater likelihood of per unit area N_2O emissions are found in Central and South America, central and western Africa, as well as parts of south and southeastern Asia (Panel 3A) – most places where upland rice is currently considered to be a dominant cultivation method. Under medium- and intense-intermittent flooding, conditions (See Table 1) however many additional regions where irrigated conditions are common become high risk (Panels 3B and 3C). When considered regionally, on the basis of total rice-harvested, the distributions of hot spots for potential N_2O emissions shifts towards regions that are large rice producers: the Asian continent finds relatively higher values, while those in the Americas recede (Panels 3D-F). Across all scenarios, certain regions of Africa (DR Congo, Ivory Coast), Asia (eastern India, Malaysia) and South America (Colombia, Ecuador) are found to be high risk. In low water-index (i.e. more aerated soils under medium and intense-intermittent flooding) conditions (Panels 3E and 3F), many more areas become potential hot spots including most of India, Indonesia, Vietnam, North and South Korea, Japan, Nigeria, southern Mali, and the Greater Caucasus.

As expected, a critical determinant of a region's susceptibility to increased rice-N_2O when medium- or intense-intermittent flooding is introduced is the proportion of rice that is actively irrigated, as opposed to deepwater or upland rice systems. If most of the rice farms in a country are upland or deepwater rice systems, the extent of flooding in that country's rice farms will change only due to changes in rainfall and/or level of local water tables but not due to changes in flooding scenarios. However, if a country has large proportions of rice farms under irrigation, different flooding regimes would actually imply changes in soil redox conditions at their rice farms and make that country susceptible to increased N_2O. With widespread adoption of these intensely-intermittent flooding scenarios for rice cultivation (without co-management of N), China might have the greatest risk of proportional increase in N_2O followed by India, Indonesia, Bangladesh, Vietnam and Brazil when compared to continuous flooding (compare Panel 3E and 3F with 3D, see also Figure 4).

Quantifying emissions across rice management classes and global rice cultivation areas indicates that under intensely-intermittent flooding, rice-N_2O could be (1.5 – 2.4 MMt-N_2O which is 2-3 times previous estimates for mild-intermittent flooding scenario (EPA, 2013) and 25-40 times larger than previous estimates for continuous flooding scenario (Gerber et al., 2016) (see Table 1 for definitions)). In contrast, our extrapolation for the mild-intermittent flooding scenario for the whole world (~830,000 tons N_2O year^{-1}) is quite close to previous estimate of 840,000 tons N_2O year^{-1} (EPA, 2013), when using a constant nitrogen inputs (N) rate of 106 kg N ha^{-1} (area-weighted average of N rates used by previous report (EPA, 2013)) as opposed to the variable rates reported by Mueller et al (2012; see appendix for further discussion). Our estimate for rice-N_2O under the continuous flooding scenario, where rice-CH_4 emissions remain high, is very small (~60,000 tons N_2O year^{-1}; Table 3) and is quite close to a previous estimate for continuous flooding (~80,000 tons N_2O year^{-1}) (Gerber et al., 2016). Obviously, a continuous flooding case does not apply to many regions of the world but we use these scenarios because they have been used by previous peer reviewed studies to establish boundaries for our estimates.

Figure 3: *Risk of elevated N_2O emissions for global rice cropland under three alternate flooding scenarios for irrigated farms across the world at region- and rice-specific N fertilizer application rates (Mueller et al. 2012). Panels A to C depict levels of risk in a per-unit area metric, while panels D to F have been adjusted to incorporate measures of harvested area of rice for each rice growing region as delineated by IRRI (2011). For panels 3A-C, the scale of the colored bar varies from zero to ~35 tons N_2O per 1.2 arc-minute (~72 kg N_2O ha^{-1} assuming a 2.2 km grid cell). For panels 3D-F, the N_2O risk levels are relative and a quantitative scale can not be assigned to the colored bar because the size of different rice growing regions is not same (IRRI, 2011). For quantitative analysis at national levels, please see Table 3.*

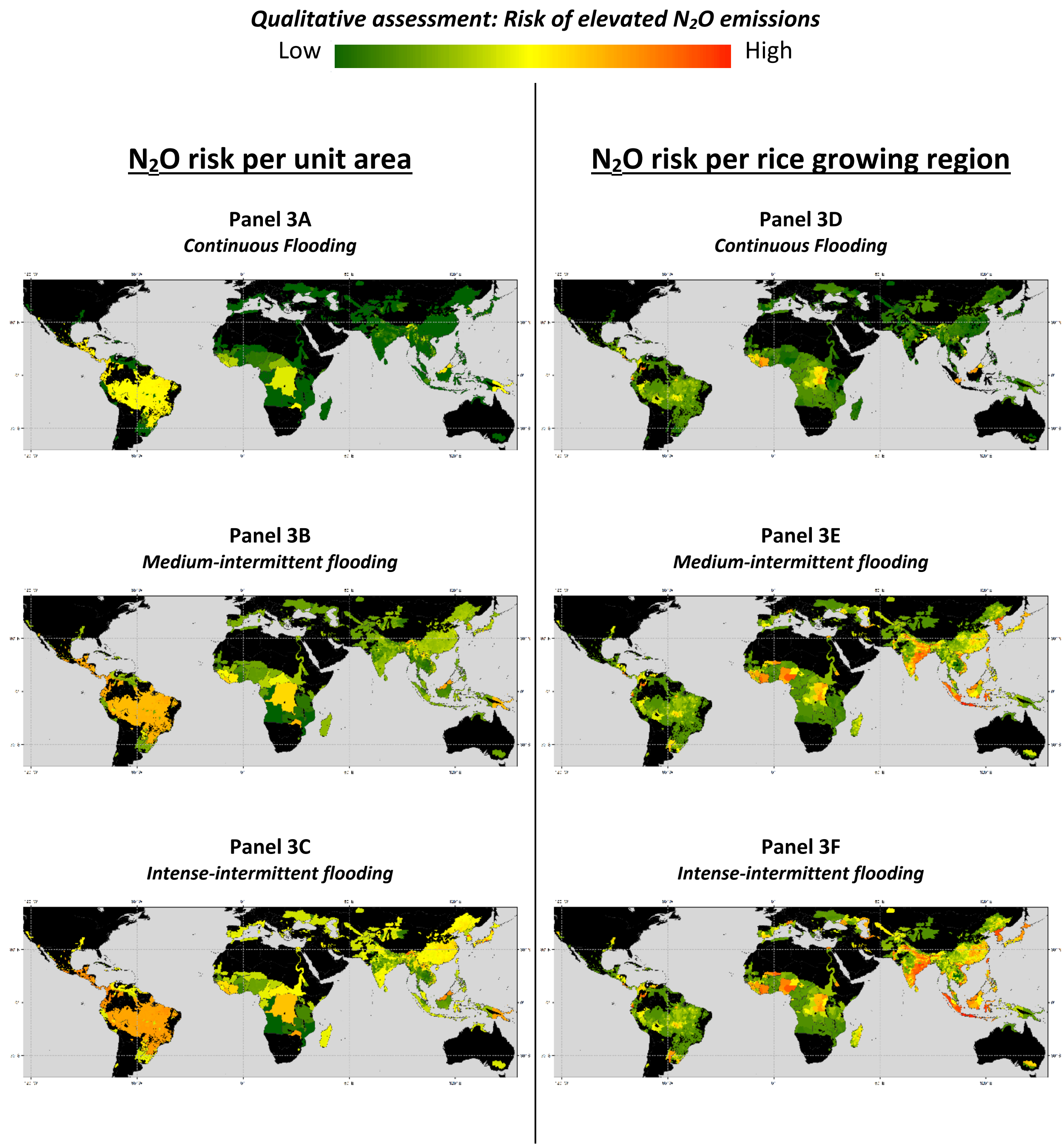


Table 2 *Estimates of rice-N_2O for different countries per unit land area based on assumptions presented in Table 1 and Figures 1-2 (see corresponding panels 3A-3C)*

Potential average rice-N_2O per unit area from rice producing countries (kg ha^{-1})			
Country	**Scenario: Per-Hectare average N_2O Emissions (kg-N_2O ha^{-1})**		
	Continuous flooding	Medium-intermittent flooding	Intense-intermittent flooding
Costa Rica	17	22	24
Honduras	16	21	23
El Salvador	15	20	22
Panama	15	20	22
Guatemala	15	20	21
Bhutan*	1	16	21
Belize	14	19	21
Brunei Darussalam	14	19	21
Nicaragua	14	19	21
Zimbabwe	14	19	20
Papua New Guinea	13	19	20
Bolivia	13	18	20
Colombia	10	17	20
Ecuador	11	17	20
Brazil	12	18	20
India*	0	13	20
Nepal*	0	12	19
Mexico	7	15	19
Liberia	12	17	18
Malaysia	5	14	18
Democratic Republic of the Congo	11	16	18
Bangladesh*	0	11	18
Peru	6	14	18
Cote d'Ivoire	9	14	16
Sri Lanka*	0	11	16
Jamaica	2	12	16
Paraguay	1	12	16
Pakistan*	0	7	15

Table 3 *Estimates of rice-N_2O for different countries (adjusted for total harvested rice area) based on assumptions presented in Table 1 and Figures 1-2 (see corresponding panels 3D-3F)*

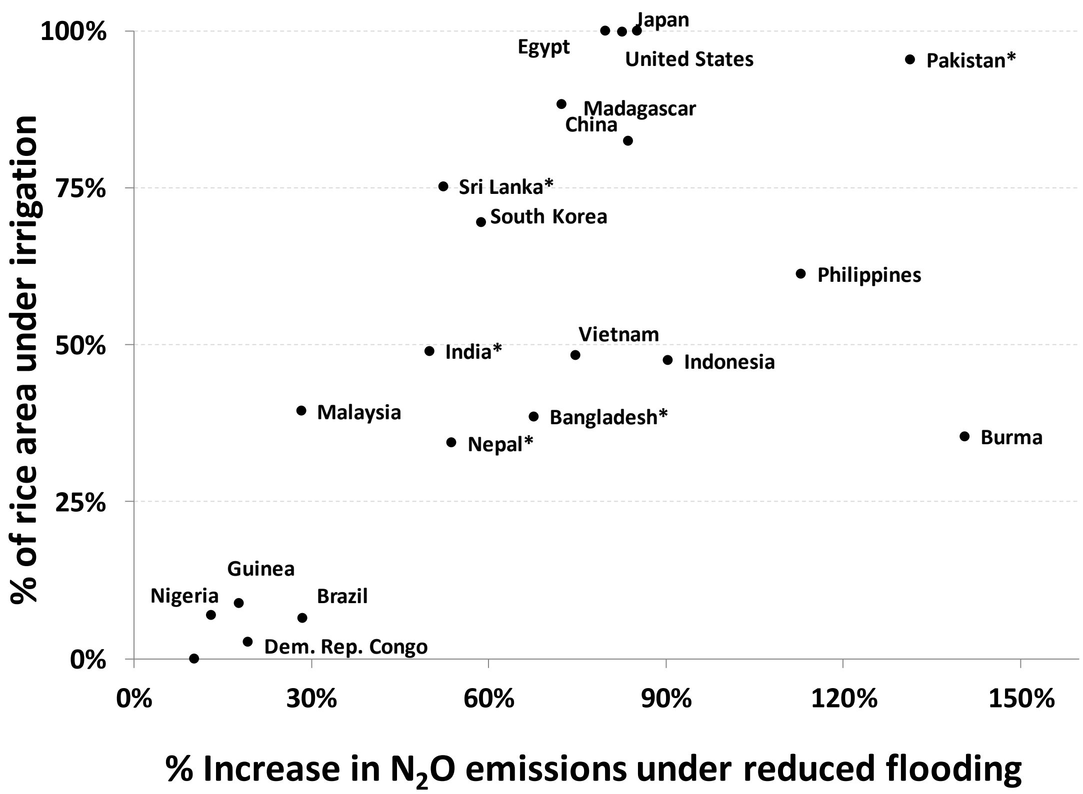
Table 3. Potential rice-N_2O from rice producing countries (million metric tons)					
Country	**Scenario: Aggregate N_2O Emissions (MMT-N_2O)**				
	Continuous flooding	Medium-intermittent flooding	Intense-intermittent flooding	Gerber (2016)	EPA (2013)
India*	0.00	0.53	0.79	0.0184	0.25
China	0.00	0.38	0.65	0.0332	0.11
Indonesia	0.00	0.09	0.16	0.0060	0.08
Bangladesh*	0.00	0.08	0.13	0.0039	0.20
Vietnam	0.00	0.06	0.10	0.0036	0.08
Brazil	0.02	0.06	0.08		
Burma	0.00	0.02	0.05		
Philippines	0.00	0.02	0.04		
Japan	0.00	0.02	0.03		
Pakistan*	0.00	0.01	0.03		
Nepal*	0.00	0.02	0.03		
United States	0.00	0.01	0.03		
Madagascar	0.00	0.01	0.02		
Korea, Republic of	0.00	0.01	0.02		
Malaysia	0.00	0.01	0.02		
Thailand	0.00	0.00	0.02		
Nigeria	0.00	0.01	0.01		
Egypt	0.00	0.01	0.01		
Cote d'Ivoire	0.01	0.01	0.01		
Sri Lanka*	0.00	0.01	0.01		
Dem. Rep. of the Congo	0.01	0.01	0.01		
Guinea	0.01	0.01	0.01		
World	**0.06**	**1.46**	**2.39**	**0.08**	**0.84**
**estimates obtained from Indian subcontinent regional analysis (Kritee et al. 2018)* *Water index and Flooding events are based on Table 1*					

Rice growing area under irrigation *vs.* potential for high N_2O emissions

Rice growing countries that have higher percentage rice under irrigation are more susceptible to high N_2O emissions under intensely-intermittent flooding regimes (see Figure 4). Countries within the Indian subcontinent are denoted by an asterisk and the results corresponding to these countries were directly derived from our previous study. This arises because higher area under irrigation implies that with intense forms of intermittent flooding, more total rice area will have lower water indices and hence higher N_2O emissions based on Equation 1. Here, irrigated area was estimated as the share of the 'irrigated' class composing total rice area, summarized by country based on IRRI (2011).

Several data points like Burma and Thailand (not shown in this figure) are found to be outliers. This is simply because the majority of the rice production in such countries is carried out in rainfed lowland conditions (with very high water index). Because overall N_2O emissions are expected to be zero under such conditions, small changes in number of flooding events$_{>3\ days}$ for the remaining rice area associated with the 'upland' and 'other' classes cause an outsized percentage change in expected N_2O emissions based on Equation 1.

Figure 4: Relationship of irrigated rice area vs. % increase in N_2O emissions risk when moving from medium (Figure 3E) to intense-intermittent (Figure 3F) flooding regime. *Scatterplot depicting relationship between variables, for nationally aggregated statistics. If different countries move from medium to intense intermittent flooding, the net susceptibility of different countries to increased N_2O emissions as calculated by Equation 1 will depend on the percentage of area under irrigation.*



Global rice cultivation: Climate impact & mitigation potential

The IPCC estimated that current climate impact of global rice cultivation is 1000-1250 MMT CO_2e_{100} year^{-1} (Smith et al., 2007). In contrast, net GHG emission estimates based on our multiple regression models for N_2O and CH_4 (Equations 1 and 2) and areas under rice management classes (IRRI, 2011) can be as high as 1930 MMT $CO_2e_{100\text{-years}}$ (or 3650 MMT $CO_2e_{20\text{-years}}$; see Appendix Table 1). Our estimates are highly dependent on the distribution of irrigated areas among various flooding regimes (continuous *vs.* mild-, medium- or intense-intermittent) both at irrigated as well as rainfed rice farms. If all the irrigated and rainfed rice growing regions were under continuous flooding, the net climate impact over long time could be at least 1500 MMT CO_2e_{100}.

However, if these irrigated rice growing regions were under intense-intermittent flooding, the current impact of global rice cultivation would be closer to 1930 MMT CO_2e_{100}. Please see Appendix Tables 1 and 2 for other intermediate scenarios.

The current mitigation potential from rice cultivation across the world according to IPCC is ~230 MMT CO_2e_{100} year^{-1} by 2030 (Smith et al., 2007). Our multiple regression model, however, estimates a higher range of annual mitigation potentials from irrigated rice farms in the world. If we assume that all the current irrigated rice farms are under continuous flooding and can be moved to mild-intermittent flooding while keeping inorganic fertilizer use constant at 150 kg N ha^{-1} which is the average recommended fertilizer use rate across the world, the mitigation potential is ~550 MMT CO_2e_{100} (or 660 MMT CO_2e_{20}; see Appendix Table 2). It is notable that most well irrigated rice farms in major rice producing countries use much higher fertilizer rates than around 150 kg N ha^{-1} with parts of China and India using as high as 400 kg N ha^{-1} (Guo et al., 2017) (See Appendix Table S3 in Kritee et al., 2018). If all irrigated rice fields are currently under intense-intermittent flooding regimes and could be moved to mild-intermittent flooding regimes while keeping fertilizer use constant at 250 kg N ha^{-1}, the mitigation potential will also be ~550 MMT CO_2e_{100} (or 1550 MMT CO_2e_{20}; Appendix Table 1). We estimate a slightly higher mitigation potential of 630 MMT CO_2e_{100} if all irrigated rice areas globally reduce fertilizer use from 250 kg N ha^{-1} to 150 kg N ha^{-1} and move from intense-intermittent flooding to mild-intermittent flooding regime (Appendix Tables 1 & 2).

Kritee et al. (2018) showed that up to 90% of climate impact from an individual rice farm in the Indian subcontinent can be mitigated through co-management of nitrogen fertilizers and organic matter with shallow (mild-intermittent) flooding. Here, our estimates based on our multiple regression model (Equations 1 and 2) imply that 50-60% of the current climate impact from irrigated rice farms across the world can be mitigated through shallow (mild-intermittent) flooding without any change in inorganic and organic fertilizers. This estimate does not include rainfed or deepwater farms.

Different short- and long-term climate impacts of different mitigation strategies

According to our model (Equations 1 and 2), two scenarios give similar net mitigation of ~550 MMT CO_2e over 100 years:

1) moving from intense-intermittent flooding to mild intermittent flooding without changing fertilizer use (Column I1- Mi2 in Appendix Table 1) and

2) moving from continuous flooding to mild-intermittent flooding while maintaining fertilizer use at 150 kg N ha^{-1} (Column C1 - Mi2 in Appendix Table 2).

While the long term mitigation over 100 years is similar, the two scenarios offer a very different short-term mitigation over 20 years. 550 MMT CO_2e_{100}/year over 100 years timeframe is equivalent to either 660 or 1550 MMT CO_2e_{20} over 20 years timeframe depending on which GHG (CH_4 vs N_2O) is reduced more significantly.

Table 4: Summary of change in understanding of climate impacts of rice cultivation

	Previous literature	After Kritee et al (2018) & this report
Empirical data		
Maximum hourly flux (μg N_2O m^{-2} h^{-1})	2,100	15,000
Maximum seasonal flux (kg ha^{-1} $season^{-1}$)	9.9	32.8
Emission factor (% of added N converted to N_2O)*	0.02 to 0.7%	0.02 to 31%
Maximum rice-N_2O Mitigation potential (tCO_2e_{100} ha^{-1})	0.3#	6
Global extrapolation		
Global rice-N_2O emissions (MMT N_20)	0.08-0.84**	1.5-2.4**
Global rice-N_2O (MMT tCO_2e_{100})	24-250**	447-715**
Global climate impact of rice cultivation (MMT tCO_2e_{100})	700-1250***	1500-1930###
Global mitigation potential (MMT tCO_2e_{100})	230	450-550##
General understanding		
Climate impacts of rice cultivaton	Short-term	Both short- and long-term
Greenhouse gases from rice fields reported to UNFCCC	CH_4	CH_4 and hopefully N_2O
Main recommended strategy to reduce rice GHG emissions	Reduce water & organic input (with a mention of N use efficieny to tackle N_2O)	Co-manage fertilizer & organic input region-specifically with central focus on water
Best water management strategy for irrigated farms	Alternate wetting and drying	Mild-intermittent or shallow flooding (without extended flooding/drainage)

** 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.** The lower range of "Before this study" is based on crop-specific dataset associated Gerber et al (2016). This range is very low because it assumes very little area under non-flooded conditions. The upper range of "Before this study" is based on EPA (2013) as explained in the main text. "After this study" estimate based on intensely-intermittent flooding scenarios where flooding regime is medium- or intense-intermittent flooding. *** Including estimates from IPCC (2007) report and EPA (2013). # 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. ## Depending on the current actual water use at irrigated farms. See Tables in Appendix of the white paper ### Based on Kritee et al (2018) and area under different management classes as presented in IRRI (2011).*

Conclusion

The geospatial analysis presented in this paper shows that the scale of N_2O emissions from rice farms across the world under intense forms of intermittent flooding could be large (1.46-2.39 MMT N_2O or 450 – 700 MMT CO_2e_{100}; Table 3). This scale is equivalent to annual CO_2 emissions from about 200 coal power plants. Put together with our estimates of CH_4 emissions (Appendix Tables 1 and 2), the net climate impact from rice farms all over the world equivalent to 600 medium sized coal power plants (~1,500-1,930 MMT $CO_{2\text{-}e100}$). The overall change of our understanding of climate impact of global rice cultivation is captured in Table 4.

We urgently need the global scientific and policy community to undertake further research to obtain high resolution flooding regime maps as well as to measure N_2O data with high sampling frequency from a wide range of intermittently flooded rice farms from different agro-ecological zones across the globe. This future research will ensure that perverse outcomes of CH_4 mitigation efforts through alternate wetting and drying do not undercut their value in the long term.

Appendix

Appendix 1: Modeling N_2O Flux

Empirical models vs. biogeochemical models

Given the resource-intensiveness of field measurements, GHG mitigation programs across the world have always looked to modeling-based approaches for quantification of GHG emission reductions over large scales. There are two types of prevailing modeling approaches:

- **Empirical models:** Linear or multiple- regression analysis is used to extrapolate existing research and data to develop regionally explicit emissions factors or equations. Such emission factors or regression equations produce GHG response curves for different management parameters (or for just nitrogen inputs in 'Tier 1' models that are limited to a farm or a very small geographic area). Our empirical model is a Tier 2 empirical model that includes management parameters other than nitrogen and includes analysis of data from multiple agro-ecological zones. Empirical models can be developed without the use of a complex biogeochemical model (which is usually much more input data-intensive) and are relatively easy and transparent to use. They do not capture the nuances of spatial and temporal variability on GHG dynamics at finer scales, and can be less flexible in handling alternative management practices which change parameters other than those included in the empirical model.

- **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:

- At a regional (Tier 2) scale, covering areas 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.

- 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.

Models for predicting rice N_2O emission rates

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 carbon offset programs and many other registries such as the Verified Carbon Standard (VCS) or Gold Standard, use empirical models to predict agricultural GHG emission reductions. We note that IPCC still uses a Tier 1 universal equation to determine N_2O emissions from upland (non-rice) crops. Our experimental results were used to develop a multiple regression derived Tier 2 empirical model with multiple parameters which we clearly consider to be an improvement over the IPCC Tier 1 emission factor for the Indian subcontinent. However, this model derived from a few farms in India should be used extremely cautiously when extrapolating outside Indian subcontinent. This is why we list our assumptions and limitations in Appendix 2.

DNDC and Daycent are the two current process based biogeochemical models that predict methane emissions in rice. The currently available latest version of Daycent model only predicts methane; not nitrous oxide emissions. 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 compared our results with. Other DNDC based studies are limited to one field or one small geographic area and cannot be extrapolated to the entire world.

Appendix 2: Limitations of Geospatial Extrapolation

Extrapolating our experimental results based on five farms in the Indian subcontinent (Kritee et al., 2018) to other rice growing regions in the world should be done with significant caution. We are encouraged, however, to present this white paper because one of the previous reports to give an estimate of global or regional rice nitrous oxide emissions (EPA, 2013) includes assumptions that are coarser than some of ours. The inorganic N input rates used in EPA study (EPA, 2013) are fixed (as compared to our region-specific fertilizer rates) as well as significantly lower than ours(Mueller et al 2012). The range of flooding regimes used earlier (EPA, 2013) is also limited as compared to the ranges explored in this white paper. Also, the EPA estimate is based on a limited empirical rice-N_2O dataset that doesn't include measurements from intensely-intermittent flooding scenarios.

Extrapolating our regression outputs at a global 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-N_2O risk assessments.

Inorganic fertilizer input dataset

The data documented in Mueller et al. (2012) depicts application rates standardized to the year 2000 (Mueller et al., 2012). Although this is the most recent globally consistent and spatially explicit data, application rates may have increased (and perhaps significantly so) in the last 18 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 did not have a way to differentiate between single rice vs double rice-rice cropping cycles. Additionally, fertilizer inputs from Mueller et al. (2012) describe total annual (and not seasonal) amounts. Nonetheless, there may be regions of the world where our estimates are less accurate due to the need to better standardize water indices to single- or 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 has not been 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(Asilo et al., 2014; Asilo et al., 2011; Boschetti et al., 2014; Chemin et al., 2012; Teluguntla et al., 2015), 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 km^2 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

Our global 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 (Kritee et al., 2018) and in turn, the dataset that generated the empirical model (Equation 1). The extrapolation in this white paper relies on the assumption that N_2O emissions scale linearly beyond the experimental range covered in Kritee et al (2018). 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. For this reason, and the higher resolution dataset depicting management types for the Indian subcontinent, we are more confident in the potential emission estimates for the Indian subcontinent presented earlier (Kritee et al. 2018), and less so for the global analysis presented in this white paper (Tables 1 and 2) where the main objective was to assess potential scale of global rice-N_2O emissions.

Appendix Table 1 Water Index & flood events assumed for estimating global climate impact of rice cultivation (Inorganic N = 250 Kg ha^{-1}, SOC = 0.4)

Rice management class	Water index	Flood events	N	CH_4 (kg/ha)	N_2O* (kg/ha)	N_2O (tCO_2e_{100}/ha)	CH_4 (tCO_2e_{100}/ha)	Total GWP (tCO_2e_{100}/ha)	Total GWP (tCO_2e_{20}/ha)	Global Area (million ha)**	Net global GWP (MMT-CO_2e_{100})	Net global GWP (MMT-CO_2e_{20})
Irrigated (Continous flooding) (C1)	500	8	250	303.9	0.0	0.0	10.3	10.3	26.1	93.4	965.1	2441.2
Irrigated (Continous flooding) (C2)	500	5	250	203.1	0.0	0.0	6.9	6.9	17.5	93.4	645.0	1631.5
Irrigated (Mild-intermittant) (Mi1)	-100	6	250	236.7	0.8	0.2	8.0	8.3	20.6	93.4	774.0	1921.5
Irrigated (Mild-intermittant) (Mi2)	-100	2	250	102.3	6.6	2.0	3.5	5.4	10.6	93.4	507.3	985.9
Irrigated (Medium-intermittant) (Me1)	-600	5	250	203.1	10.1	3.0	6.9	9.9	20.2	93.4	926.0	1884.3
Irrigated (Medium-intermittant) (Me2)	-600	0	250	35.1	17.3	5.2	1.2	6.3	7.7	93.4	592.6	714.8
Irrigated (Intense-intermittant) (I1)	-1200	3	250	135.9	22.4	6.7	4.6	11.3	17.7	93.4	1055.1	1652.5
Irrigated (Intense-intermittant) (I2)	-1200	0	250	35.1	26.7	8.0	1.2	9.2	10.2	93.4	855.1	950.8
Upland (U)	-1500	0	250	35.1	31.4	9.4	1.2	10.6	11.4	14.7	154.7	167.6
Lowland rainfed/Deepwater (W1)#	500	1	250	68.7	0.0	0.0	2.3	2.3	5.9	48.4	113.2	286.2
Lowland rainfed/Deepwater (W2)#	800	12	250	438.3	0.0	0.0	14.9	14.9	37.7	48.4	721.8	1825.8

** Neglecting negative nitrous oxide emissions. ** IRRI (2011) # There is a large range of flooding regimes experienced by rainfed farms in the world.*

	Net global GWP (MMT-CO_2e_{100})	Net global GWP (MMT-CO_2e_{20})
Maximum global GHG emissions from irrigated areas assuming intense-intermittent flooding (I1)	1055.1	1652.5
Minimum global GHG emisisons from irrigated areas assuming mild-intermittent flooding (Mi2)	507.3	985.9
Lowest baseline emissions assuming 100% of the irrigated farms have continuous flooding (U+W1+C2)	912.9	2085.4
Baseline emissions assuming 100% of the irrigated and rainfed farms have continuous flooding (U+W2+C2)	1521.5	3624.9
Highest baseline emissions assuming 100% of the irrigated farms have intense-intermittent flooding (U+W2+I1)	1931.6	3645.9
Global mitigation : Assuming 100% irrigated farms have continuous flooding today and there is no change in N or organic matter use (C1 - Mi2)	457.8	1455.3
Global mitigation : Assuming 100% irrigated farms have intense-intermittent flooding today and there is no change in N or organic matter use (I1 - Mi2)	547.8	666.6

Appendix Table 2 Water Index & flood events assumed for estimating global climate impact of rice cultivation (Inorganic N = 150 Kg ha^{-1}, SOC = 0.4)

Rice management class	Water index	Flood events	N	(kg/ha) based	N_2O* (kg/ha)	N_2O (tCO_2e_{100}/ha)	CH_4 (tCO_2e_{100}/ha)	Total GWP (tCO_2e_{100}/ha)	Total GWP (tCO_2e_{20}/ha)	Global Area (million ha)**	Net global GWP (MMT-CO_2e_{100})	Net global GWP (MMT-CO_2e_{20})
Irrigated (Continous flooding) (C1)	500	8	150	303.9	0.0	0.0	10.3	10.3	26.1	93.4	965.1	2441.2
Irrigated (Continous flooding) (C2)	500	5	150	203.1	0.0	0.0	6.9	6.9	17.5	93.4	645.0	1631.5
Irrigated (Mild-intermittant) (Mi1)	-100	6	150	236.7	0.0	0.0	8.0	8.0	20.4	93.4	751.7	1901.4
Irrigated (Mild-intermittant) (Mi2)	-100	2	150	102.3	3.4	1.0	3.5	4.5	9.7	93.4	419.8	907.2
Irrigated (Medium-intermittant) (Me1)	-600	5	150	203.1	7.0	2.1	6.9	9.0	19.3	93.4	838.6	1805.6
Irrigated (Medium-intermittant) (Me2)	-600	0	150	35.1	14.1	4.2	1.2	5.4	6.8	93.4	505.2	636.1
Irrigated (Intense-intermittant) (I1)	-1200	3	150	135.9	19.3	5.7	4.6	10.4	16.9	93.4	967.6	1573.8
Irrigated (Intense-intermittant) (I2)	-1200	0	150	35.1	23.6	7.0	1.2	8.2	9.3	93.4	767.6	872.1
Upland (U)	-1500	0	150	35.1	28.3	8.4	1.2	9.6	10.6	14.7	141.0	155.3
Lowland rainfed/Deepwater (W1)#	500	1	150	68.7	0.0	0.0	2.3	2.3	5.9	48.4	113.2	286.2
Lowland rainfed/Deepwater (W2)#	800	12	150	438.3	0.0	0.0	14.9	14.9	37.7	48.4	721.8	1825.8

** Neglecting negative nitrous oxide emissions. ** IRRI (2011) # There is a large range of flooding regimes experienced by rainfed farms in the world.*

	Net global GWP (MMT-CO_2e_{100})	Net global GWP (MMT-CO_2e_{20})
Maximum global GHG emissions from irrigated areas assuming intense-intermittent flooding (I1)	967.6	1573.8
Minimum global GHG emisisons from irrigated areas assuming mild-intermittent flooding (Mi2)	419.8	907.2
Lowest baseline emissions assuming 100% of the irrigated farms have continuous flooding (U+W1+C2)	899.2	2073.1
Baseline emissions assuming 100% of the irrigated and rainfed farms have continuous flooding (U+W2+C2)	1507.8	3612.6
Highest baseline emissions assuming 100% of the irrigated farms have intense-intermittent flooding (U+W2+I1)	1830.4	3554.9
Global mitigation : Assuming 100% irrigated farms have continuous flooding today and there is no change in N or organic matter use (C1 - Mi2)	545.3	1534.0
Global mitigation assuming irrigated farms have intense-intermittent flooding, no change in SOC but N use decrease from 250 to 150 kg N ha^{-1} (I1, previous table - Mi2)	635.3	745.2

References

Alam, M.S., Islam, M.A., Mia, M.D., Akteruzzaman, M.D., 2011. Assessing The Effect Of Arsenic Contamination On Modern Rice Production: Evidences From A Farm Level Study. Bangladesh J. Agric. Econ., 34(1-2): 15-28.

Asilo, S. et al., 2014. Complementarity of Two Rice Mapping Approaches: Characterizing Strata Mapped by Hypertemporal MODIS and Rice Paddy Identification Using Multitemporal SAR. Remote Sensing, 6(12): 12789-12814.

Asilo, S. et al., 2011. Automated mapping of rice paddies using multitemporal MODIS images. Philippine Journal of Crop Science (Philippines).

Boschetti, M., Nutini, F., Manfron, G., Brivio, P.A., Nelson, A., 2014. Comparative analysis of normalised difference spectral indices derived from MODIS for detecting surface water in flooded rice cropping systems. PLoS ONE, 9(2).

Carlson, K.M. et al., 2017. Greenhouse gas emissions intensity of global croplands. Nature Climate Change, 7(1): 63-68.

CCAC, 2014. Methane mitigation in rice paddies: A new CCAC component. A joint announcement brochure by CGIAR Research Program on Climate Change, Agriculture, and Food Security (CCAFS) and Climate and Clean Air Coalition (CCAC) to Reduce Short-Lived Climate Pollutants. International Rice Research Institute.

CCAFS, 2017. Mitigation strategies in rice production, in collaboration with the Climate and Clean Air Coalition (CCAC). In: The CGIAR Research Program on Climate Change, A.a.F.S. (Editor), Low emissions development research flagship. Wageningen University & Research, The Netherlands.

Chemin, Y., Phuphak, S., Asilo, S., Hijmans, R.J., others, 2012. Determining spatial and temporal patterns of submergence in rice with MODIS satellite data. International Journal of Geoinformatics, 8(2): 1.

Ciais, P. et al., 2014. Carbon and other biogeochemical cycles. In: Stocker, T.F. et al. (Eds.), Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

EPA, 2013. Global Mitigation of Non-CO_2 Greenhouse Gases: 2010-2030, United States Environmental Protection Agency, Washington DC.

Erenstein, O., 2009. Comparing water management in rice–wheat production systems in Haryana, India and Punjab, Pakistan. Agr. Water Manage., 96(12): 1799-1806.

Gerber, J.S. et al., 2016. Spatially explicit estimates of N_2O emissions from croplands suggest climate mitigation opportunities from improved fertilizer management. Glob. Change Biol., 22(10): 3383-3394.

GRiSP, 2013. Rice Almanac by Global Rice Science Partnership: 4th Edition. International Rice Research Institute, Los Baños (Philippines), 283 pp.

Guo, J. et al., 2017. The rice production practices of high yield and high nitrogen use efficiency in Jiangsu, China. Scientific Reports, 7: 2101.

Hobbs, P.R., L.W. Harrington, C. Adhikarv, G.S. Giri, S,R. Upadhyay, B. Adhikary, 1996. Wheat and Rice in the Nepal Tarai: Farm resources and production practices in Rupandehi sistrict. Nepal Agricultural Research Council (NARC) and International Maize and Wheat Improvement Center (CIMMYT), Mexico.

Hou, A.X., Chen, G.X., Wang, Z.P., Van Cleemput, O., Patrick, W.H., 2000. Methane and Nitrous Oxide Emissions from a Rice Field in Relation to Soil Redox and Microbiological Processes. Soil Science Society of America Journal, 64(6): 2180-2186.

IRRI, 2011. Global Rice Area: Data obtained from International Rice Research Institute's Social Sciences Division in January 2016, derived from World Rice Statistics Online at: http://ricestat.irri.org:8080/wrs2/entrypoint.htm.

Johnson-Beebout, S.E., Angeles, O.R., Alberto, M.C.R., Buresh, R.J., 2009. Simultaneous minimization of nitrous oxide and methane emission from rice paddy soils is improbable due to redox potential changes with depth in a greenhouse experiment without plants. Geoderma, 149(1–2): 45-53.

Kirschke, S. et al., 2013. Three decades of global methane sources and sinks. Nature Geosci., 6(10): 813-823.

Kritee, K. et al., 2018. High nitrous oxide fluxes from rice indicate the need to manage water for both long- and short-term climate impacts. Proc. Natl. Acad. Sci. doi: 10.1073/pnas.1809276115

Lagomarsino, A., A.E. Agnelli, B. Linquist, M.A.A. Adviento-Borbe, A. Agnelli, G. Gavina, and M. Ravaglia, 2016. Alternate wetting and drying of rice reduced CH_4 but triggered N_2O peaks in a clayey soil of central Italy. Pedosphere, 26(4): 533-548.

Li, X., Yuan, W., Xu, H., Cai, Z., Yagi, K., 2011. Effect of timing and duration of midseason aeration on CH_4 and N_2O emissions from irrigated lowland rice paddies in China. Nutr. Cycl. Agroecosys., 91(3): 293-305.

Linquist, B.A., Adviento-Borbe, M.A., Pittelkow, C.M., van Kessel, C., van Groenigen, K.J., 2012. Fertilizer management practices and greenhouse gas emissions from rice systems: A quantitative review and analysis. Field Crop. Res. , 135: 10-21.

Mueller, N.D. et al., 2012. Closing yield gaps through nutrient and water management. Nature, 490(7419): 254-257.

Myhre, G. et al., 2013. Anthropogenic and Natural Radiative Forcing. In: Stocker, T.F. et al. (Eds.), Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Pereira, L., Cai, L., Musy, A., Mao, Z., 2000. Issues for water-savings in north China irrigated agriculture. Proceedings of the International Conference on Ecosystem Service and Sustainable Watershed Management in North China.

Richards, M., Ole-Sander, B., 2014. Alternate wetting in drying in irrigated rice: Implementation guide for policymakers and investors as pratice brief on Climate Smart Agriculture, Copenhegan

Sass, R.L., 2003. CH_4 Emissions from Rice Agriculture., IPCC Expert Meetings on Good Practice Guidance and Uncertainty Management in National Greenhouse Gas Inventories. Institute for Global Environmental Strategies (IGES) for the IPCC Hayama, Japan, pp. 399-417.

Smith, P. et al., 2007. Agriculture. In: Metz, B., Davidson, O.R., Bosch, P.R., Dave, R., Meyer, L.A. (Eds.), Climate Change 2007: Mitigation. Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA. .

Suryavanshi, P., Singh, Y., Prasanna, R., Bhatia, A., Shivay, Y., 2013. Pattern of methane emission and water productivity under different methods of rice crop establishment. Paddy Water Environ., 11(1-4): 321-329.

Teluguntla, P., Ryu, D., George, B., Walker, J.P., Malano, H.M., 2015. Mapping Flooded Rice Paddies Using Time Series of MODIS Imagery in the Krishna River Basin, India. Remote Sensing, 7(7): 8858-8882.

Turner, A. et al., 2016. A large increase in US methane emissions over the past decade inferred from satellite data and surface observations. Geophys. Res. Lett. , 43: 2218–2224.