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Model comparison and quantification of nitrous oxide emission and mitigation potential from maize and wheat fields at a global scale

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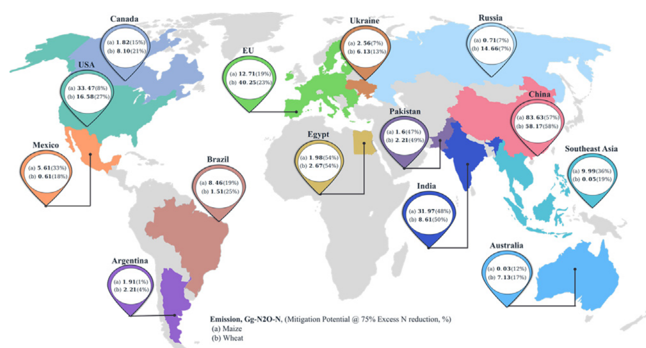
HIGHLIGHTS

- Area-scaled N_2O emissions from maize and wheat fields are higher in Asia and Europe but lower in Africa and South America.
- Country total N_2O emissions from maize and wheat fields are greater in East and South Asia than other regions.
- N_2O emissions in maize and wheat fields are driven mainly by higher N application rates.
- Countries with high yields of maize and wheat have lower emission intensity compared to those with low yields.
- Excess nitrogen management offers huge opportunity for N_2O emission reduction and achieving national mitigation targets.

GRAPHICAL ABSTRACT



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ABSTRACT

Maize and wheat are major cereals that contribute two-thirds of the food energy intake globally. The two crops consume about 35% of the nitrogen (N) fertilizer used in agriculture and thereby contribute to fertilizer-induced nitrous oxide (N_2O) emissions. Thus, estimation of spatially disaggregated N_2O emissions from maize and wheat fields on a global scale could be useful for identifying emission and mitigation hotspots. It could also be needed for prioritizing mitigation options consistent with location-specific production and environmental goals. N_2O emission from four models (CCAFS-MOT, IPCC Tier-I, IPCC Tier-II and Tropical N_2O) using a standard gridded dataset from global maize and wheat fields were compared and their performance evaluated using measured N_2O emission data points (777 globally distributed datapoints). The models were used to quantify spatially disaggregated N_2O emission and mitigation potential from maize and wheat fields globally and the values were compared. Although the models differed in their performance of capturing the level of measured N_2O emissions, they produced similar spatial patterns of annual N_2O emissions from maize and wheat fields. Irrespective of the models, predicted N_2O emissions per hectare were higher in some countries in East and South Asia, North America, and Western Europe, driven mainly by higher N application rates. The study indicated a substantial

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Mitigation
Wheat

N_2O abatement potential if application of excess N in the maize and wheat systems is reduced without compromising the yield of the crops through technological and crop management innovations. N_2O mitigation potential is higher in those countries and regions where N application rates and current N_2O emissions are already high. The estimated mitigation potentials are useful for hotspot countries to target fertilizer and crop management as one of the mitigation options in their Nationally Determined Contributions (NDCs) to the United Nations Framework Convention on Climate Change (UNFCCC).

1. Introduction

Global crop production is facing the greatest challenge of increasing food production by more than 70% to meet an expected 34% increase in the world population by 2050 (Alexandratos and Bruinsma, 2012; Tilman et al., 2011). Achieving this goal will lead to increased use of fertilizers, particularly nitrogen-based fertilizers (van Beek et al., 2010), thereby leading to increased greenhouse gas (GHG) emissions. On the other hand, most countries in the world are committed to implementing the Paris Agreement, which aims at substantially reducing global greenhouse gas emissions to limit global temperature increase to below 2 °C above pre-industrial levels, and countries are looking for the best GHG mitigation options across all sectors, including agriculture.

Mineral nitrogen fertilizer is the single largest nitrogen input in croplands, accounting for almost half of global nitrogen input (Liu et al., 2010). However, only a portion of applied reactive nitrogen (N) is converted into food, while the rest is lost through different pathways such as ammonia volatilization, nitrate leaching and denitrification (Cassman et al., 2002; Tilman et al., 2002). The portion of applied N that is not taken up by crops is responsible for causing environmental problems, besides increasing producers' costs. Estimates show that about 77% of total anthropogenic nitrous oxide (N_2O) is emitted from agricultural soils or cropped fields, and is mainly produced by nitrification and denitrification processes of N in the soil (IPCC, 2019a; Wrage et al., 2001). Agriculture is the largest (63%) consumer of annual terrestrial N (Sutton et al., 2013), and application of N for fertilization is a cause of massive environmental problems on a global scale (Liu et al., 2016). Thus, mitigating the environmental impact of N fertilizer consumption while increasing crop production to feed the rising population is the major challenge faced by current and future agriculture. Given the situation, the use of fertilizers, particularly N-based ones in intensive crop production systems and the associated increase in N_2O emissions, has been a subject of intensive scientific investigation at the global or regional scale lately (Bodirsky et al., 2014; Fowler et al., 2013; Houlton et al., 2019; Lassaletta et al., 2016; Liu et al., 2016; Shcherbak et al., 2014; Wang et al., 2017; Wu et al., 2014; Zhang et al., 2015).

Accordingly, considerable efforts have been devoted to developing models and tools that simulate N_2O emissions from soil. Some models are process-based (e.g., DNDC, DAYCENT, Ecosys, NLOSS, WNMM, Expert-N, and NASA CASA), while others (e.g., ALU, Cool Farm Tool or CCAFS-MOT, EX-ACT, IPCC Tier methods, etc.) are empirical calculators (Colomb et al., 2013). In all cases, large uncertainties still remain when trying to estimate the large-scale GHG budget mainly because of differences in estimation methods and limited data availability (Zhang et al., 2018). Recently, more empirical and mechanistic models have been developed and used to estimate global N_2O emissions from soil as a result of N fertilizer application (Tian et al., 2018). The reason behind the popularity of empirical models is mainly because they require less data and yet responsive to the soil, climate and management systems that mostly control N_2O emissions.

Process-based models are dynamic and can capture the complex agroecosystem interactions for estimating N_2O emissions from agricultural fields (Grant et al., 2020; Khalil et al., 2016), but they are data intensive which limit their large-scale use. Few authors have compared the performance of various process-based models (e.g., DayCENT, DLEM, DNDC, DyN, NOE, NGAS, and EPIC) for estimating N_2O emission as a function of N management strategies (Gaillard et al., 2018; Khalil et al., 2016). The studies found substantial model differences for simulating N_2O emissions and showed underestimation of N_2O emissions by the models when compared with measurement data (Gaillard et al., 2018). However, comparison of empirical models for estimating N_2O emissions from cropland as a function of fertilizer management is scanty. This is partly due to lack of consistent data that can be used across models and spatial scales in the past.

Maize (*Zea mays* L.) and wheat (*Triticum aestivum* L.), major cereals grown on about 415 million ha of cultivated land, comprise about two-thirds of the world's food energy intake (FAOSTAT, 2019). Maize and wheat account for the first and second largest global consumption of all fertilizer N among the major cereals, respectively (Heffer et al., 2017). The two crops consume ca. 35% of total N fertilizer applied to crops globally (IFA and IPNI, 2017) and contribute a significant portion of fertilizer-induced N_2O emissions (Dhadli et al., 2016).

Better fertilizer and crop management systems in maize and wheat fields provide tremendous opportunities to reduce fertilizer N application without compromising yield, thereby contributing to low N_2O emissions besides reducing farmers' production costs. Thus, developing effective policies for mitigating N_2O emissions from maize and wheat fields requires a quantitative understanding of the level of N fertilizer use and N_2O emissions and their spatial distribution. Moreover, developing effective mitigation policies requires dependable N_2O emission estimates from models with known uncertainties. However, information on spatially explicit N_2O emissions from maize and wheat fields on a global scale is largely lacking. The objectives of this study were, therefore, to evaluate N_2O emissions of four empirical models (CCAFS-MOT, IPCC Tier-I, IPCC Tier-II and Tropical N_2O) using field measured data and estimate N_2O emission and mitigation potential at a global scale using common input data from maize and wheat fields. We mapped the global distribution of N_2O emissions, identified emission hotspots and mitigation potentials, and linked this analysis to the countries' policy response addressing agricultural emissions.

2. Methodology

The study focused on evaluating and comparing four commonly used empirical N_2O estimation methods (Tropical N_2O model, CCAFS-MOT, IPCC Tier-I and IPCC Tier-II). The models were selected based on similarities in input data requirements, data availability, level of complexity and demonstrated or potential use in both developed and developing regions. In terms of data, the focus of the study was to establish a standard dataset at a global level for an objective comparison of N_2O estimates by each model on a global scale.

2.1. Data types and sources

Several global datasets were obtained from different sources and processed to the required unit and spatial resolution (Table 1).

2.1.1. Crop productivity, harvest area and season length

Crop specific production area and crop yield were obtained from the annual total harvested area, product of the Spatial Production Allocation Model (IFPRI, 2019). The harvested area has a resolution of five arc

Table 1
Data types used for running the N_2O estimation models.

Data type	Original resolution (degrees)	Database period	Model requiring the data	Data source	Supplementary material (S)
Crop area (ha)	0.0833	2010	All models	(IFPRI, 2019)	S1
Crop yield (kg ha ^{1})	0.0833	2010	All models (to derive N from crop residue)	(IFPRI, 2019)	S2
Crop duration (days)	0.0833	Mean (1961–1990)	Tropical-N_2O	(IIASA/FAO, 2012)	S3
Synthetic N fertilizer rate (kg ha ^{1})	0.50	2013	All models	(Lu and Tian, 2017)	S4, S5
Manure N application (kg ha ^{1})	0.0833	2013	All models	(Zhang et al., 2017)	S6
Crop residue fraction returned to soil	0.0833	–	All models	Calculated	S7
N from crop residue	0.0833	2010	All models	Calculated	S8
Soil texture class (FAO/UNESCO)	0.0833	2014	CCAFS-MOT	(Shangguan et al., 2014)	S14, S15
Percentage area of organic soils	0.0833	2016	IPCC Tier-I, IPCC Tier-II (to derive N supply from mineralization)	(Tubiello et al., 2016)	S9
Soil organic carbon stock loss (t ha ^{1})	0.0833	1990–2010		(Sanderman et al., 2018a)	S10
C:N ratio	0.0833	2012		(FAO/IIASA/ISRIC/ISS-CAS/JRC, 2012)	S11
Soil organic carbon (%)	0.00833	2017	CCAFS-MOT	(Sanderman et al., 2018a)	S12
Soil pH	0.00833	2017	CCAFS-MOT	(Hengl et al., 2017)	S13
Clay	0.00833	2017	Used to derive USDA soil texture class (Tropical-N_2O)	(Hengl et al., 2017)	
Silt	0.00833	2017		(Hengl et al., 2017)	
Sand	0.00833	2017		(Hengl et al., 2017)	
Climate zones	0.0833	2010	CCAFS-MOT, IPCC Tier-I, IPCC Tier-II	(JRC-EC, 2010)	S16
Excess N in croplands (kg ha^{-1})	0.0833	2013	–	(West et al., 2014)	S17

minutes (~0.0833° × 0.0833°; Table 1), represents the area from where a crop is harvested, and accounts for multiple harvests of a crop grown on the same grid. When there are multiple harvests, the harvest area can be larger than the physical crop area in each pixel because of multiple harvests of a crop on the same physical area.

Data on the length of the cropping season were obtained from the Global Agro-ecological Zones (GAEZ v3.0) crop calendar dataset (IIASA/FAO, 2012). In the GAEZ, cropping season length in a given grid is determined by identifying the sowing date that leads to the highest attainable yield of a given crop (IIASA/FAO, 2012). To estimate N_2O emissions, the cropping season length was limited to between 90 and 300 days to match the realistic growing season boundaries of maize and wheat.

2.1.2. Nitrogen fertilizer

2.1.2.1. Synthetic N fertilizers. The global time series gridded data on annual synthetic N use in agricultural lands with horizontal resolution of 0.5° × 0.5° (Lu and Tian, 2017) were used to derive grid-specific N application rates. The N rates were classified into N sources using the historical country-level N fertilizer consumption by product obtained from the International Fertilizer Association (IFA) dataset for the 1961–2015 period (IFADATA, 2017). Nitrogen fertilizers were aggregated into three main categories (ammonium nitrate, urea and other N fertilizers). The average percentage fraction of N use in each fertilizer group from the total direct N consumption was estimated for each country using the following equation:

$$NPF_x = \left(\frac{CN_x}{CN_{total}}\right) * 100 \tag{1}$$

where NPF_x is the percentage fraction of N use for x fertilizer type; CN_x is N use for x fertilizer type in tones and CN_{total} is total N use in tones.

The N fertilizer use rate for each fertilizer group was obtained by multiplying the country level fertilizer use fraction by the grid-level total N use rate.

2.1.2.2. Organic N fertilizers. The common organic N fertilizer sources are manure and crop residue. Data on application of N from manure were obtained from a 0.0833° grid global dataset (Zhang et al., 2017). The datasets from the Global Livestock Impact Mapping System (GLIMS) in conjunction with country-specific annual livestock population (Gilbert et al., 2018) were used to reconstruct manure N production to agricultural fields. The manure N applied to cropland was developed based on the manure management system in three livestock production systems: rangeland-based systems, mixed rain-fed farming systems, and mixed irrigated farming systems for cattle (dairy and other cattle), goats and sheep, and poultry and swine (smallholder and industrial systems). Crop residue production was calculated by multiplying crop yield data by a crop-specific residue conversion factor (dry weight ratio of straw to grain). Due to regional differences in management, a region-specific residue recycling factor was used to estimate the residue biomass return to soil. These factors account for residue burning, removal and other non-cropland human uses (Conant et al., 2013). Crop residue N inputs for maize and wheat production were determined by multiplying the estimate of residue production by residue N concentration (Lal, 2005) for each crop and region-specific recycling factor.

2.1.3. Soil properties

High resolution (0.00833° x 0.00833°) soil property data such as soil organic carbon (SOC), pH, texture of the top (0–30 cm) soil layer were obtained from the International Soil Reference and Information Centre (Hengl et al., 2017). Global carbon (C) stock data (Sanderman et al., 2018b) were used to estimate the average annual C loss. Annual rates of C stock change were estimated as the difference in carbon stocks of the year 2010 relative to the carbon stock of a reference year (1990) divided by the time dependence of the stock change factors (S15).

The annual net N mineralized because of SOC loss was estimated using the carbon to nitrogen (CN) ratio of the soil organic matter. A default value of 10 was used for grid points with missing CN values involving management changes on croplands. The annual area of managed/drained organic soils was calculated by multiplying the global distribution of percentage fraction of Histosols dataset (Tubiello et al., 2016) multiplied by the emission factor.

The soil pH values used ranged from 3.5 to 9.0. Any values out of this range were set to either the minimum, if the values were below the range, or to the maximum limit, if the values were above the range, except for sodic soils. The soil textures of the surface layer were estimated based on the USDA soil texture classification from sand, clay and silt contents (Gerakis and Baer, 1999; Soil Survey Division Staff, 1993).

2.1.4. Climate classification

The IPCC world climate zone map was acquired from Joint Research Centre (JRC) of the European Commission (EC)(JRC-EC, 2010). The JRC agro-climatic zone map defines climatic zones by considering annual mean temperature, total annual precipitation, total annual potential evapotranspiration (PET) and elevation.

2.1.5. Excess N balance from croplands

The N-balance was estimated based on a simple mass balance principle using the annual amount of N-input and N-output (West et al., 2014). Thus, the excess N was obtained as the difference between annual N input to the soil and the amount of N harvested for the year 2013 (for details of the calculation see Supplementary material S26).

2.1.6. Estimation of annual N_2O emissions

A global grid with a horizontal resolution of 5-arcminutes (~0.0833 × 0.0833 degrees) was used to estimate annual N_2O-N emission rates per unit cropland area from maize and wheat fields. Annual N_2O emissions were estimated using the four empirical models considered for the study. Annual synthetic N fertilizer rates applied, manure deposited and residue returned to soil were used to derive the fertilizer-induced emission (FIE) of N_2O. FIE was calculated as the proportion of N fertilizer directly released as N_2O-N after discounting background soil emissions, i.e., emissions from unfertilized control plots (Bouwman, 1996; Bouwman et al., 2002; Eichner, 1990; Stehfest and Bouwman, 2006).

2.1.7. Description of models

2.1.7.1. Tropical N_2O model. This empirical statistical model simulates direct N_2O emissions from agricultural systems in tropical and subtropical regions using a Generalized Additive Mixed Model (GAMM) which allows the effects of multiple covariates to be modeled as linear or smooth non-linear continuous functions(Albanito et al., 2017a; de Klein et al., 2020; Dorich et al., 2020; Sapkota et al., 2021). The model was developed based on the data from tropical and sub-tropical (30° North and 30° South latitude) regions and provides tropic specific annual N_2O emission factors (N_2OEFs).

In this model, N_2O emission is mainly controlled by five factors, namely, crop type, study length, soil texture, fertilizer type, and N rate (Eq. 2).

$$\begin{aligned} y^{0.3}_{net-N2O-N} = {} & \alpha + f_1\,(Study\ length : Crop\ type) \\ & + f_2\,(Soil\ Texture, ''re'') + \beta_1(Fertilizer\ type : N\ rate) \\ & + \beta_2(\,N\ rate) + \beta_3(Crop\ Type) \\ & + (1 \mid Country \mid Study\ ID \mid Exp.ID) \end{aligned} \tag{2}$$

where $ynet^{0.3}$-N_2O-*N)* is the net N_2O-N emission transformed by taking the cube root; *Study length* refers to cropping duration; *Soil Texture* refers to USDA soil textural classes*; Fertilizer type* refers to fertilizer product type (ammonium nitrate, urea, organic fertilizer such as manure and residue and other N fertilizers); *N rate* refers to applied N rate for each fertilizer product type; *Crop Type* refers to the type of crop considered (annual non flooded crops, flooded rice and perennial crops), and *Country/Study ID/Exp.ID* refers to experiment identity nested under study identity in a study location. In this model, net N_2O-N emission (kg-N ha^{-1}) is calculated as the difference between the N_2O emissions in a given N input or fertilizer treatment and its respective zero-fertilizer control.

2.1.7.2. CCAFS Mitigation Option Tool (CCAFS-MOT). The CGIAR Research Program on Climate Change, Agriculture and Food Security Mitigation Options Tool (CCAFS-MOT) integrates several empirical models to estimate GHG emissions from croplands and to provide information about the most effective mitigation options(Feliciano et al., 2017; Morales et al., 2019; Varinderpal-Singh et al., 2020). This tool considers soil organic content, pH, texture, climate zone, crop type, crop yield, cropping season length, synthetic and organic N fertilizer application for estimating N_2O emission. In addition, crop management practices such as residue management, tillage, cover cropping and their duration, and organic fertilizer (compost, manure, or residue) use and method of application are considered in the estimation of emissions. The multivariate empirical model used by CCAFS-MOT is the following:

$$\log\,(N_2O-N) = A + \sum_{i=1}^{n} E_i * E_f * N_{applied} \tag{3}$$

where N_2O-N is the amount of N_2O expressed in kg ha^{-1} of N over the time period covered by the measurements, A is a constant and E_i is the effect value for factors *i* (SOC, soil pH, soil texture, climate, crop type and length of experiment). E_f is the factor for N fertilizer input, which is 0.0038.

2.1.7.3. IPCC Tier I and Tier II. The IPCC methods are developed for estimating direct N_2O emissions from managed soils. In this study, we used the IPCC Tier-I and Tier-II methods (IPCC, 2019b, IPCC, 2013, IPCC, 2006a) to estimate N_2O emissions using human-induced net N additions to soils. This includes addition of synthetic and organic fertilizers, as well as mineralization of N in soil due to drainage management of organic soils, or cultivation of mineral soils. In its most basic form, direct N_2O emissions from managed soils are estimated using the equations indicated below.

Tier-I

$$N2O-N_{Direct} = N2O-N_{N-inputs} + N2O-N_{os} \tag{4}$$

Thus,

$$\begin{aligned} N2O-N_{N-inputs} = {} & [(F_{SN} + F_{ON} + F_{CR} + F_{SOM}) * EF_1] \\ & + [(F_{SN} + F_{ON} + F_{CR} + F_{SOM})_{FR} * EF_{1FR}] \end{aligned} \tag{5}$$

$$N2O-N_{OS} = \left[\left(F_{OS,CG,Temp} * EF_{2CG,Temp}\right) + \left(EF_{OS,CG,Trop} * EF_{2CG,Trop}\right)\right] \tag{6}$$

where

$N_2O - N_{Direct}$ = annual N_2O-N emissions produced from managed soils, kg-N_2O-N yr^{-1},

$N_2O - N_{N-inputs}$ = annual N_2O-N emissions from N inputs to managed soils, kg-N_2O-N yr^{-1},

$N_2O - N_{OS}$ = annual N_2O-N emissions from managed organic soils, kg-N_2O-N yr^{-1},

F_{SN} = annual amount of synthetic fertilizer N applied to soils, kg-N yr^{-1},

F_{ON} = annual amount of animal manure N additions applied to soils, kg-N yr^{-1},

F_{CR} = annual amount of N in crop residue returned to soils, kg-N yr^{-1},

F_{SOM} = annual amount of N in mineral soils that is mineralized, in association with loss of soil C from soil organic matter as a result of changes to land use or management, kg-N yr^{-1},

F_{OS} = annual area of managed/drained organic soils, ha, (the subscripts CG refer to cropland),

EF_1 = emission factor for N_2O emissions from N inputs, 0.01 kg-N_2O-N (kg-N input)$^{-1}$,

$EF1_{FR}$ = emission factor for N_2O emissions from N inputs to flooded rice (FR), kg N_2O–N (kg N input)$^{-1}$.

EF_2 = emission factor for N_2O from drained/managed organic soils, kg-N_2O-N ha^{-1} yr^{-1} (the subscripts CG refer to cropland). Values of EF_2 for drained cropland, over boreal and temperate climate is 13 kg-N_2O-N ha^{-1} yr^{-1}, and over tropical and subtropical climate it is 5 kg-N_2O-N ha^{-1} yr^{-1} (IPCC, 2013b).

Tier-II
In Tier-II, the following equation is used to estimate direct N_2O estimation from fields:

$$N_2O_{Direct}-N = \sum_i (F_{SN} + F_{ON})_i * EF_{1i} + (F_{CR} + F_{SOM}) * EF_1 + (N_2O-N)_{OS} \quad (7)$$

where EF_{1i} = emission factors developed for N_2O emissions from synthetic fertilizer and organic N application under conditions i (kg N_2O–N (kg N input)$^{-1}$); $i = 1 \ldots$n. Details on the calculation of each component of Eq. (7) are available in the IPCC report (IPCC, 2013; IPCC, 2006a).

IPCC Tier II is the default method in national-level GHG inventories based on the guidelines provided by IPCC (IPCC, 2006a), its supplement (IPCC, 2013) and its refinement(IPCC, 2019b). The method relates direct N_2O emissions to the amount of N fertilizer applied using emission factors specific to a given country or land use. Although this method is relatively easy to implement in combination with nationwide economic statistics, it cannot be used directly to define crop management strategies that would help mitigate N_2O emissions as it does not account for the effect of fertilizer N application on crop growth and yield.

2.1.8. Model evaluation

The estimates predicted by the models were compared with N_2O data extracted from previous publications made available through the global N_2O database (https://samples.ccafs.cgiar.org/n2o-dashboard/). A total of 777 datapoints (their distribution shown in supplementary S18), 481 from maize fields and 296 from wheat fields, with less than 366/365 days of experimental length, compiled from peer-reviewed publications between 1981 and 2014 were used for model evaluation. The database provides not only N_2O emission from field measurements but also the soil and crop types, climate, fertilizer types, and application rates, methods and timing of N fertilizer application.

N_2O emissions were estimated from all four models using soil, climate and management information from the site-years as in measured data in the database. Then statistical measures were used to compare the measured and estimated N_2O emissions. The statistical indices used were the root mean square error (RMSE), normalized root mean square error (NRMSE%), percent bias (PBIAS), and the index of agreement (d).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{x}_i - x_i)^2} \quad (8)$$

The Normalized Root Mean Square Error (−100% ≤ NRMSE ≤ 100%), normalized by the range of observations is given by:

$$NRMSE = 100 * \frac{RMSE}{(x_{max} - x_{min})} \quad (9)$$

Percent bias (PBIAS) measures the average tendency of the simulated values to be larger or smaller than the observed values. The optimal value of PBIAS is 0.0, with values closer to zero indicating better model performance. Positive values indicate overestimation bias, whereas negative values indicate model underestimation bias.

$$PBIAS = 100 * \frac{\sum_{i=1}^{n}(\hat{x}_i - x_i)}{\sum_{i=1}^{n} x_i} \quad (10)$$

The Index of Agreement (d) is a standardized measure of the degree of model prediction error and varies between 0 and 1 (Willmott, 1981). A value of one indicates a perfect match, and 0 indicates no agreement. The index of agreement can detect additive and proportional differences in the observed and simulated means and variances. However, it is overly sensitive to extreme values due to the squared differences (Legates and McCabe, 1999; Moriasi et al., 2007).

$$d = 1 - \left[\frac{\sum_{i=1}^{n}(\hat{x}_i - x_i)^2}{\sum_{i=1}^{n}\left[\left(\left|\hat{x}_i - \left(\frac{1}{n}\sum_{i=1}^{n} x_i\right)\right| + \left|x_i - \left(\frac{1}{n}\sum_{i=1}^{n} x_i\right)\right|\right)^2\right]}\right] \quad (11)$$

where

n is the total validation observations,
x_i is the true (observed) value of validation observation 'i',
$\hat{x}_i$ is the predicted value of validation observation 'i'.

2.1.9. Estimation of N_2O mitigation potential

The excess N data (see Section 2.1.5) were used to estimate the N_2O mitigation potential from maize and wheat fields assuming that excess N application was reduced by increasing NUE through different management and technological innovations. Optimum synthetic N application (N_{opt}), an application that does not cause excess N, was obtained by subtracting the excess N application (N_{exc}) from the actual application (N_{act}), which is give as:

$$N_{opt} = N_{act} - N_{exc} \quad (12)$$

The mitigation potential (N_2O_{mit}) was quantified by subtracting the N_2O emission estimated using the optimum N input (N_2O_{opt}) from the emission estimated using the actual N input (N_2O_{act}) as follows:

$$N_2O_{mit} = N_2O_{act} - N_2O_{opt} \quad (13)$$

Since several factors determine the control of excess N in agriculture, the mitigation potential was estimated at different level of excess N reduction (25, 50, 75 and 100%). These different levels considered may represent the different levels of management and technological innovations used by different countries to reduce excess N from their maize and wheat fields. For the sake of brevity, the mitigation potential at 75% of excess N is presented in the main body of the paper.

2.1.10. Estimation of emission intensity

Emission intensity was obtained as the ratio of estimated N_2O emission per ha to the yield of maize and wheat per ha for the year 2010. The year 2010 was selected for estimating the emission intensity because of the availability of yield data at the required spatial resolution.

3. Results

3.1. Evaluation of global annual N_2O emissions

Agreements between measured and simulated N_2O emissions using the four methods were fairly good with the normalized root mean square error (NRMSE), index of agreement (d) and percent bias (PBIAS) values ranging between 17.3% and 21.6%, 0.48 and 0.58, and −60.9% and 7.7%, respectively (Fig. 1). However, as shown by the lowest PBIAS (−60.9%) and d (0.48) values and the highest NRMSE (21.6%), the CCAFS-MOT consistently underestimated N_2O emissions from both maize and wheat fields (Fig. 1a). Compared to measured emission values, the tropical-N_2O and IPCC Tier-I models did well (PBIAS <7.7%; NRMSE <21%; d > 0.55) in general but tended to overestimate N_2O emissions under low emission conditions from both maize and wheat fields while underestimating values under high emission conditions, particularly from maize fields (Fig. 1b & d). Compared to the three N_2O estimation methods, the IPCC Tier-II method showed a relatively better relationship with measured data (PBIAS = 5.8%; NRMSE = 19.5%; d = 0.58) from both maize and wheat fields (Fig. 1c). The model ensemble showed good agreement with the measured data

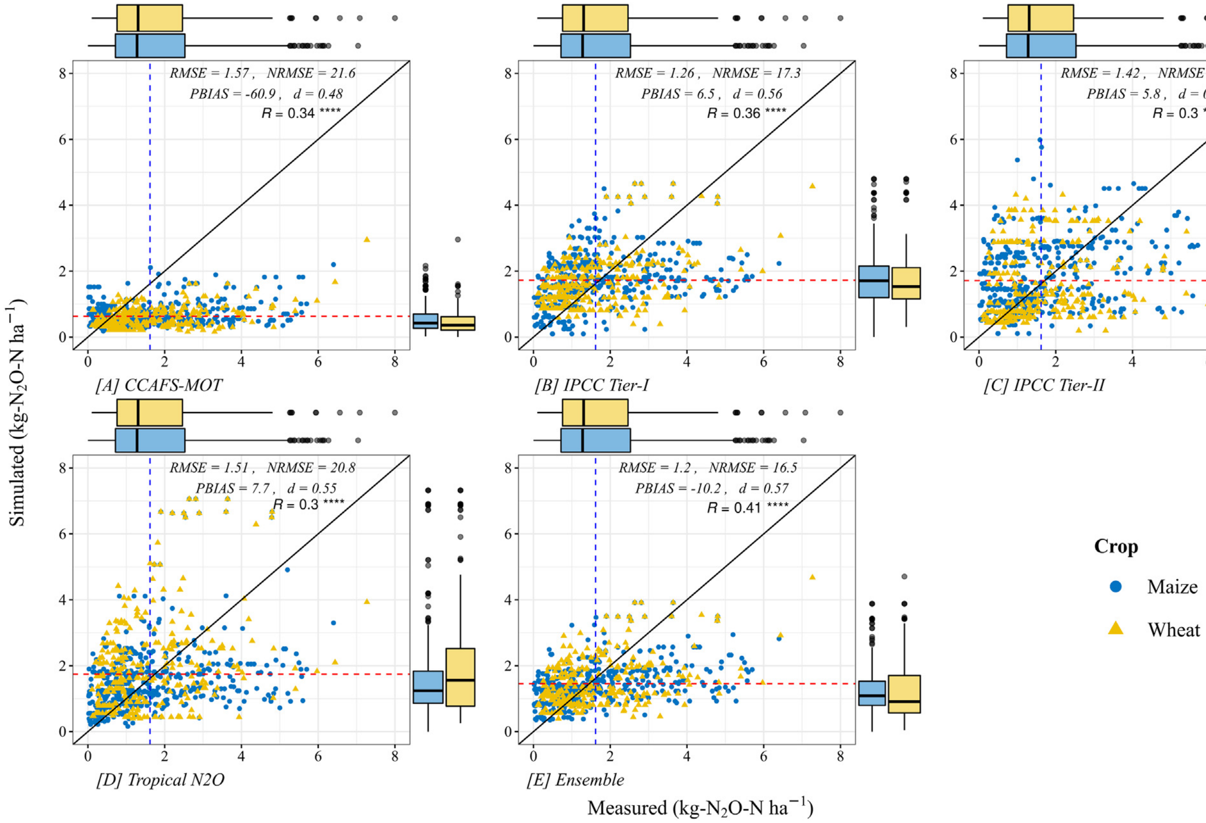

Fig. 1. Comparison of simulated annual N_2O emissions from four models and their ensemble with field measurements from maize and wheat fields.

with a lower NRME value (16.5%) compared to the individual models, although it tended to underestimate (PBIAS = −10.2%) emissions above 2 kg-N_2O-N ha^{-1} in both maize and wheat fields (Fig. 1e). In general, the model evaluation results showed that except for the CCAFS-MOT, which considerably underestimated emissions from both maize and wheat fields, the three empirical models (IPCC Tier-II, IPCC Tier-I and Tropical-N_2O) and particularly their ensemble mean performed well compared to field-measured N_2O emissions.

3.2. Global distribution of annual N_2O emissions

N_2O emissions estimated from global maize and wheat fields for the year 2013 using the CCAFS-MOT, IPCC Tier-I, IPCC Tier-II and Tropical N_2O models are presented in S18 and S19 in the Supplementary materials. Despite the difference in the magnitude of emissions (highest for IPCC Tier-1 and lowest for CCAFS-MOT), the models produced similar spatial patterns of annual N_2O emissions per ha across maize and wheat fields globally. According to the model ensemble results, area-scaled N_2O emissions from maize fields were found to be highest in East and South Asia, where N_2O emissions exceeded 3.0 kg-N_2O-N ha^{-1}, followed by some areas in Western Europe, North America, and South America (Fig. 2a). Similarly, wheat fields in East and South Asia had the highest N_2O emissions, followed by those in Northwestern Europe and North America (Fig. 2b). Large areas of maize and wheat fields in Africa, Eastern Europe and South America had relatively lower (<1.0) N_2O emissions per unit area (Fig. 2 a & b). Some maize growing countries like China, Germany, Belarus, Belgium, and Egypt, and wheat growing countries like Ireland, Switzerland, Netherland, Estonia, and Belarus had higher levels of N_2O emission per unit area than other countries (Fig. 2a & b).

The global average area-scaled N_2O emissions ranged between 0.7 kg-N_2O-N ha^{-1} (CCAFS-MOT) and 1.4 kg-N_2O-N ha^{-1} (Tropical-N_2O model) for maize fields, and between 0.7 and 1.5 kg-N_2O-N ha^{-1} for wheat fields. Based on the amount of N fertilizer applied, N fertilizer-induced N_2O emission factors from CCAFS-MOT, IPCC Tier-1, IPCC Tier-II and Tropical-N_2O were, respectively, 0.8%, 1.0%, 0.9% and 2.2%, for maize fields, and 0.5%, 1.0%, 0.8% and 1.7% for wheat fields.

Estimates of average continental area-scaled N_2O emissions (kg N_2O-N ha^{-1}) from maize and wheat fields are shown in Fig. 3. Despite model differences in the magnitude of estimates, average N_2O emissions across maize and wheat fields were generally higher in Asia and Europe but lower in Africa and South America. Model comparison showed that IPCC Tier-I had the highest N_2O emissions in Asia and Europe, while Tropical-N_2O had the highest emissions in North America, South America, Africa and Oceania (Fig. 3). The CCAFS-MOT model gave the lowest emissions on all continents except Africa. Unlike the results from other continents, the CCAFS-MOT model estimated higher N_2O emissions than IPCC Tier I & II in maize (Fig. 3a) and IPCC Tier II in wheat (Fig. 3b) in Africa. The IPCC Tier-II model gave an intermediate emission estimate which was consistently lower than IPCC Tier-I and Tropical N_2O models but higher than CCAFS-MOT across continents (Fig. 3).

Country level total N_2O emissions from maize and wheat fields are presented as bar charts for the top four countries per continent in Fig. 2. Although the magnitude of estimates varies among the models, there is general agreement among the models when identifying the major emission hotspot countries in each continent (see supplementary materials S18 and S19 for details), which is summarized by the model ensemble results. Compared to other regions, the major N_2O emission hotspots for both maize and wheat are in countries located in East and South Asia. China followed by India, Indonesia and the Philippines were the major emitters of N_2O from maize and wheat fields both in the Asian continent and globally. Based on the model ensemble values, China's annual total N_2O emissions in 2013 reached 60 Gg (giga gram = 10^9 g) and 40 Gg N_2O-N for maize and wheat, respectively (Fig. 2 a & b). China's emissions constituted 24% and 19% of the average global total

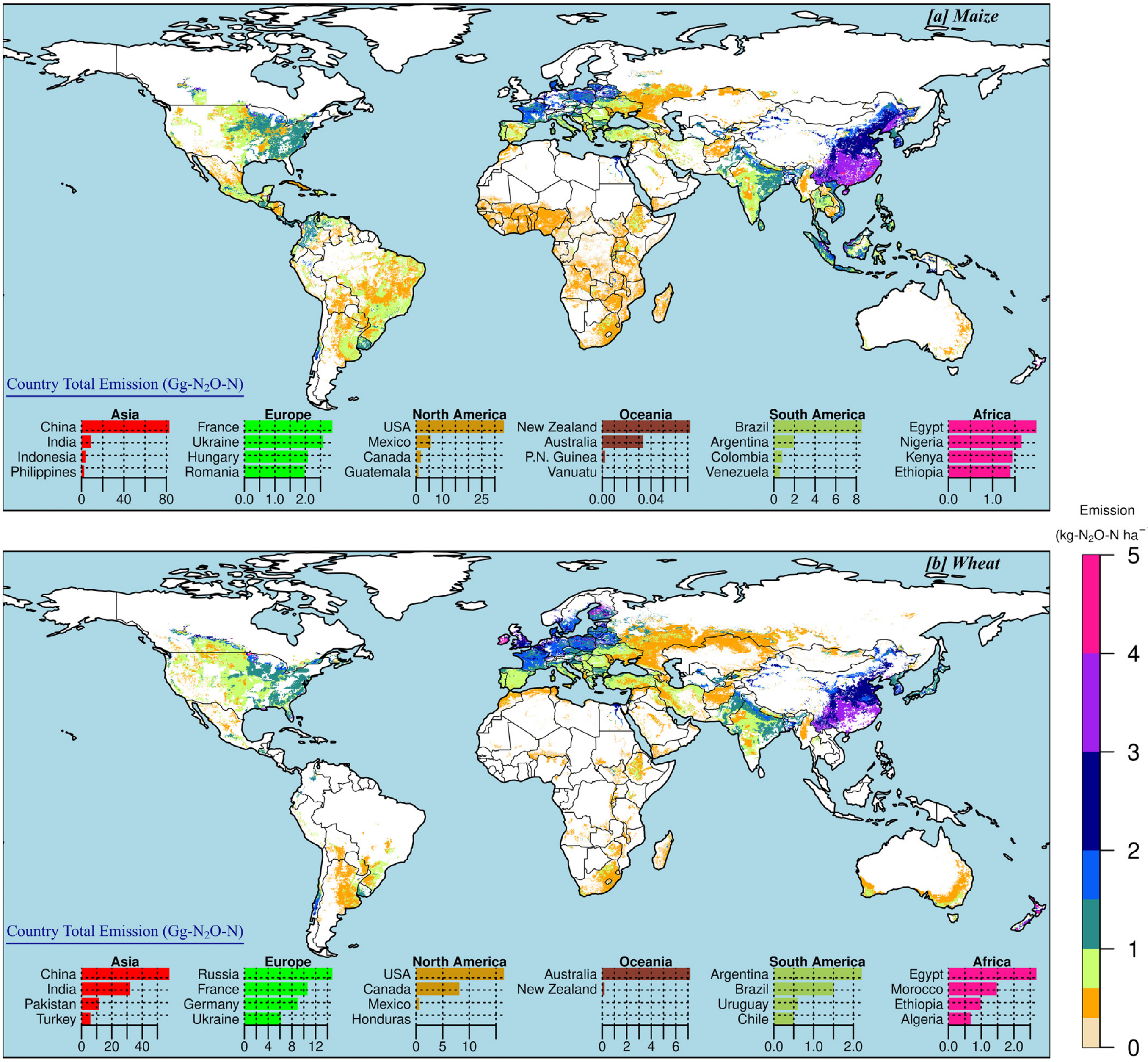

Fig. 2. Spatial distribution of annual N_2O emissions (kg-N_2O-N ha^{-1}) from (a) maize and (b) wheat fields, and annual country total emissions in Gg N_2O-N (bar charts) estimated using an ensemble of four empirical models.

N_2O emissions of 166 and 206 Gg N_2O-N from maize and wheat fields, respectively. Within Europe, Ukraine, France, Hungary, and Romania were the top countries with higher total annual N_2O emissions from their total maize area. On the other hand, Russia, France, and Germany produced the largest annual total N_2O emissions from wheat areas in Europe (Fig. 2b). In the North American region, the USA followed by Mexico had the highest total annual N_2O emissions from maize areas, whereas N_2O emissions from wheat fields were the highest in the USA followed by Canada. New Zealand and Australia, respectively, produced the highest maize and wheat annual total N_2O emissions in the Oceania region. In South America, Brazil and Argentina had the highest total annual N_2O emissions at the country level from the two crops (Fig. 2). In Africa, Nigeria and Egypt followed by Ethiopia and South Africa were the countries with the highest levels of N_2O emissions from maize fields (Fig. 2a), while Egypt and Morocco produced the major share of N_2O emissions from wheat fields (Fig. 2b).

3.3. Global distribution of emission intensity

We found large variations in N_2O emission intensity across the maize and wheat growing areas globally based on the model ensemble results (Supplementary material S20). In maize, emission intensity was significantly ($P < 0.05$) correlated with area-scaled emission ($r = 0.34$), N application rate ($r = 0.20$) and yield ($r = -0.33$). Similarly, wheat emission intensity was significantly ($P < 0.05$) correlated with both area-scaled N_2O emission ($r = 0.45$), N rate ($r = 0.22$) and yield ($r = -0.29$). Accordingly, countries with high yield of maize (e.g., Netherlands, Belgium, Germany, Spain and Chile) and wheat (e.g., Ireland, Netherlands, Belgium, UK and Germany) had lower emission intensity compared to other countries (e.g., Botswana, Zimbabwe, Panama, and Costa Rica for maize and Vietnam, Ecuador, Colombia, Jordan, and Honduras for wheat) with lower yield and higher emission intensity (Fig. 4).

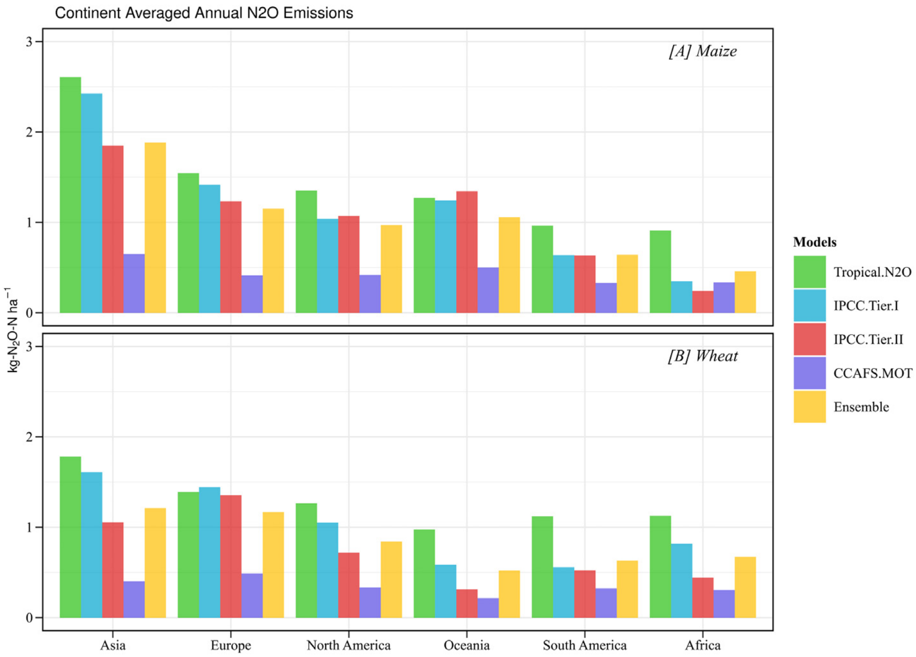

Fig. 3. Continental average annual N_2O emissions (kg-N_2O-N ha^{-1}) from (a) maize and (b) wheat fields estimated using four empirical methods.

3.4. Fertilizer N rate and potential for N_2O mitigation

N fertilizer rate for maize and wheat across the countries ranged from less than 5 kg ha^{-1} to 300 kg ha^{-1}. China and Egypt are the countries that apply the highest amount of N fertilizer (~ 300 kg ha^{1}) to their maize and wheat fields (Fig. 5). Some major producer countries in Asia (Vietnam, North Korea, Bangladesh and India), Europe (Germany, Poland and France) and North America (USA) apply 100–200 kg ha^{-1} N fertilizer to their maize fields (Fig. 5a). Similarly, there is a wide range of N fertilizer application among the major wheat producers with Belgium applying more than 200 kg ha^{-1} and UK, Germany, Poland, France, Check Republic, Uzbekistan, Bangladesh, Pakistan and India applying 100–150 kg N ha^{-1} (Fig. 5b). Some major wheat growing countries in Africa and South America and Russia in Europe apply less than 50 kg ha^{-1} synthetic N to their fields (Fig. 5b).

The N balance data derived from the global dataset show that several countries have excess N-balance from their maize and wheat fields (S17). The intensive maize and wheat production systems in China, Egypt, Pakistan and North India have the highest excess N balance (S17).

Assuming that at least 75% of excess N can be reduced without compromising yield through various fertilizer management strategies, the ensemble (Fig. 6) and all the models (see Supplementary materials S21 and S22) indicate huge N_2O mitigating potential in major maize and wheat growing regions and countries. Based 75% excess N reduction, the global N_2O mitigation potential from maize and wheat fields was 70 and 85 Gg N_2O—N, respectively. This is equivalent to 36% and 35% reduction of total global N_2O emissions from maize and wheat production, respectively. The highest N_2O mitigation potential from maize fields was observed in China, followed by major producer countries like India, USA, Mexico, Brazil, Indonesia, Philippines, and Egypt (Fig. 6a). Similarly, the models estimated considerable potential for N_2O emission reduction from wheat fields in China and India followed by Pakistan, USA, France, Germany, UK, Turkey, Canada, and Egypt (Fig. 6b). The results, in general, show that the maize and wheat fields in the regions or countries where N_2O emissions were very high (Fig. 2) are also the areas with the highest potential for N_2O emission reduction (Fig. 6). In other words, N_2O emission hotspot countries also possess considerable mitigation potential from maize and wheat fields.

4. Discussion

This study compared simulated N_2O emissions from four empirical models, and evaluated the performance of each model against measured data compiled from publications with respect to the models' ability to capture the spatial variability of annual N_2O emissions and responses to N application rates from maize and wheat fields. For the first time, this study compared four empirical N_2O emission estimation models on a global scale using a standard gridded input dataset with fine spatial resolution.

4.1. Model performance and comparison

Although it is difficult to accurately predict N_2O emissions from agricultural soils because of several drivers and complex interactions, the empirical models evaluated in this study (CCAFS-MOT IPCC Tier-I, IPCC Tier II and Tropical-N_2O) generally captured the variations of measured N_2O emissions reasonably. However, some discrepancies between measured and model-estimated N_2O emissions were observed as measurements were conducted at the site level, while model estimations and input data were at the grid level with a spatial scale of ~10 km × 10 km. Therefore, part of the relative discrepancies between model estimations and measured data could be due to scale mismatch (point vs. grid) between the datasets. The models failed to capture the higher N_2O emissions (> 4 kg-N2O-N ha^{-1}) which negatively affected the evaluation statistics. The models also struggled to reproduce the observed N_2O measurements over locations where measured N_2O emissions were higher due to higher background emissions from soil. Despite these limitations, the empirical models fairly described the pattern of N_2O emissions from N fertilized maize and wheat fields. Similar to previous model comparison efforts (Gaillard et al., 2018), we also evaluated the use of a multi-model ensemble which outperformed individual model estimations.

With respect to individual model performance, however, there was a considerable difference between the four empirical models. The N_2O emission estimates from IPCC models, particularly Tier-II, had better agreement with the observed data. This could be partly due to the capability of the IPCC models to account for all the major N sources (IPCC, 2019b; IPCC, 2013; IPCC, 2006b), namely, synthetic fertilizer, manure, crop residue and mineralized N from maize and wheat fields, as

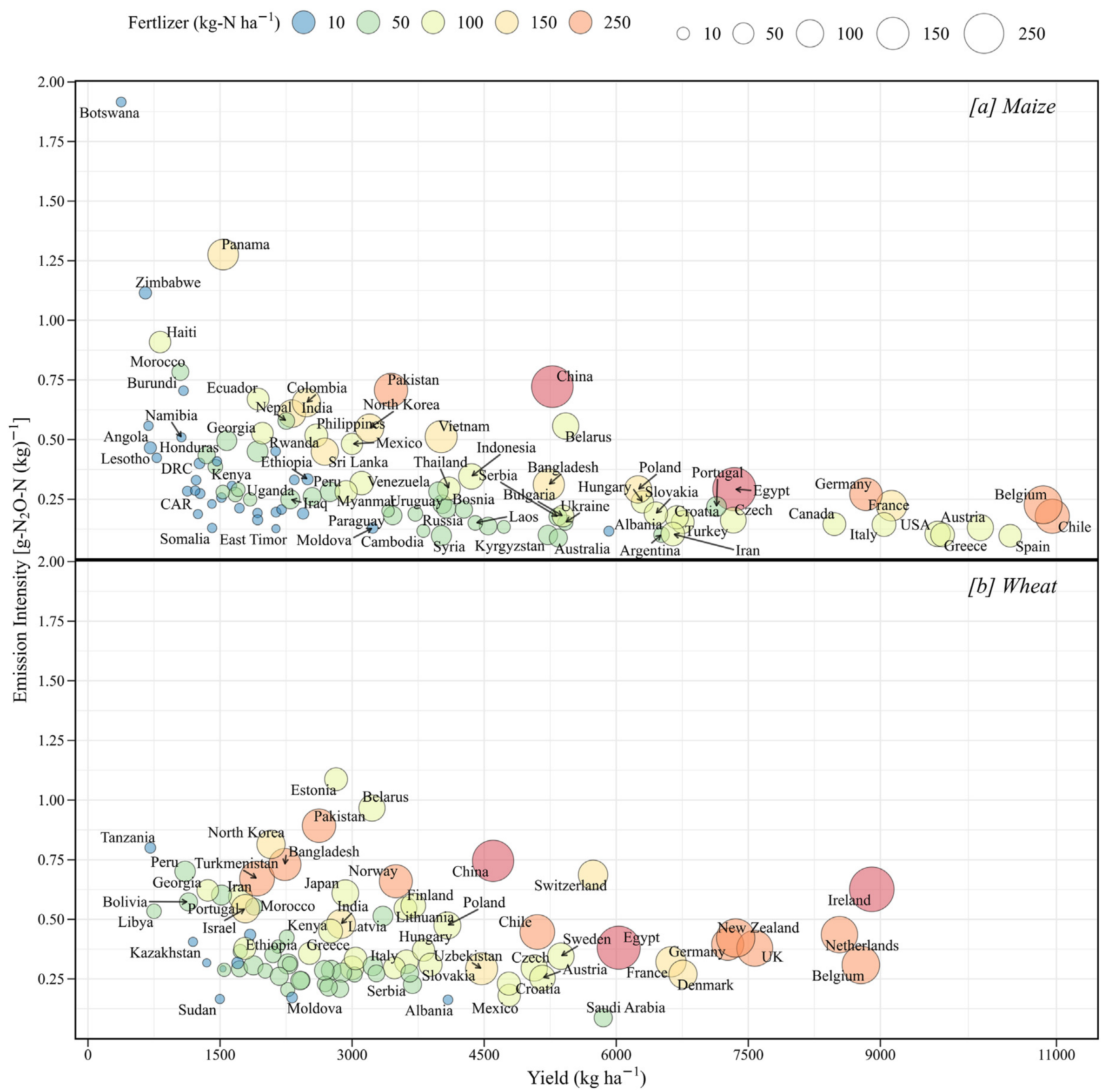

Fig. 4. Emission intensity of (a) maize and (b) wheat growing countries in relation to yield and N application rates.

compared to CCAFS-MOT (Feliciano et al., 2017) and Tropical N_2O (Albanito et al., 2017a) models which do not account for N released through soil mineralization. Compared to measured data and estimates from the rest of the models, CCAFS-MOT consistently underestimated N_2O emissions from both maize and wheat fields globally, except in Africa. The relatively low global emissions from CCAFS-MOT was mainly due to lower emission factor (0.0038) for N fertilizer inputs in CCAFS-MO (Feliciano et al., 2017; Stehfest and Bouwman, 2006) than the three other studied models. CCAFS-MOT also underestimates N_2O emissions from the cultivation of drained organic soils that are known for enhanced mineralization of N-rich organic matter which increases N_2O emissions. The relatively higher N_2O emission estimated by CCAFS-MOT across Africa could be due to its higher factor for fine textured soils (0.4312), which are dominant in the region, particularly in Eastern Africa.

Compared to the three models, the Tropical-N_2O model estimated higher N_2O emissions from maize and wheat fields with a global average FIE value of 2.2% and 1.7%, respectively. These values were comparable to the ones reported by Albanito et al. (Albanito et al., 2017b) from tropical agro-ecosystems, i.e., 2.1% for croplands fertilized with ammonium nitrate (NH_4NO_3), 1.1% for cropland fertilized with other N-fertilizer sources and 0.7% for cropland fertilized with urea and nitrification inhibitors. The Tropical-N_2O model disaggregates N-fertilizer by source and also considers the effect of the study length which could have contributed to the model's better performance at lower values of N_2O (~< 3 kg-N_2O-N ha^{-1}) than the other models (Albanito et al., 2017a). Although the model was developed using tropical data, the performance of the model in temperate regions was much better than expected (Supplementary material S23).

The comparison of the four N_2O models at global and regional levels shows that the results vary with the use of individual model. This variation might lead to over- or underestimation of N_2O emissions that can misinform policymakers when designing the GHG mitigation target and prioritizing mitigation options for a given region or location. However, the analysis indicates that an N_2O emission estimation model can be best suited for a given region or condition depending on the applied emission factors and other parameters considered in the models. For example, CCAFS-MOT performed better under low emission conditions, while it underestimated emissions in high (>2 kg-N_2O-N ha^{-1}) emission areas relative to measured data. The IPCC Tier-II model performed

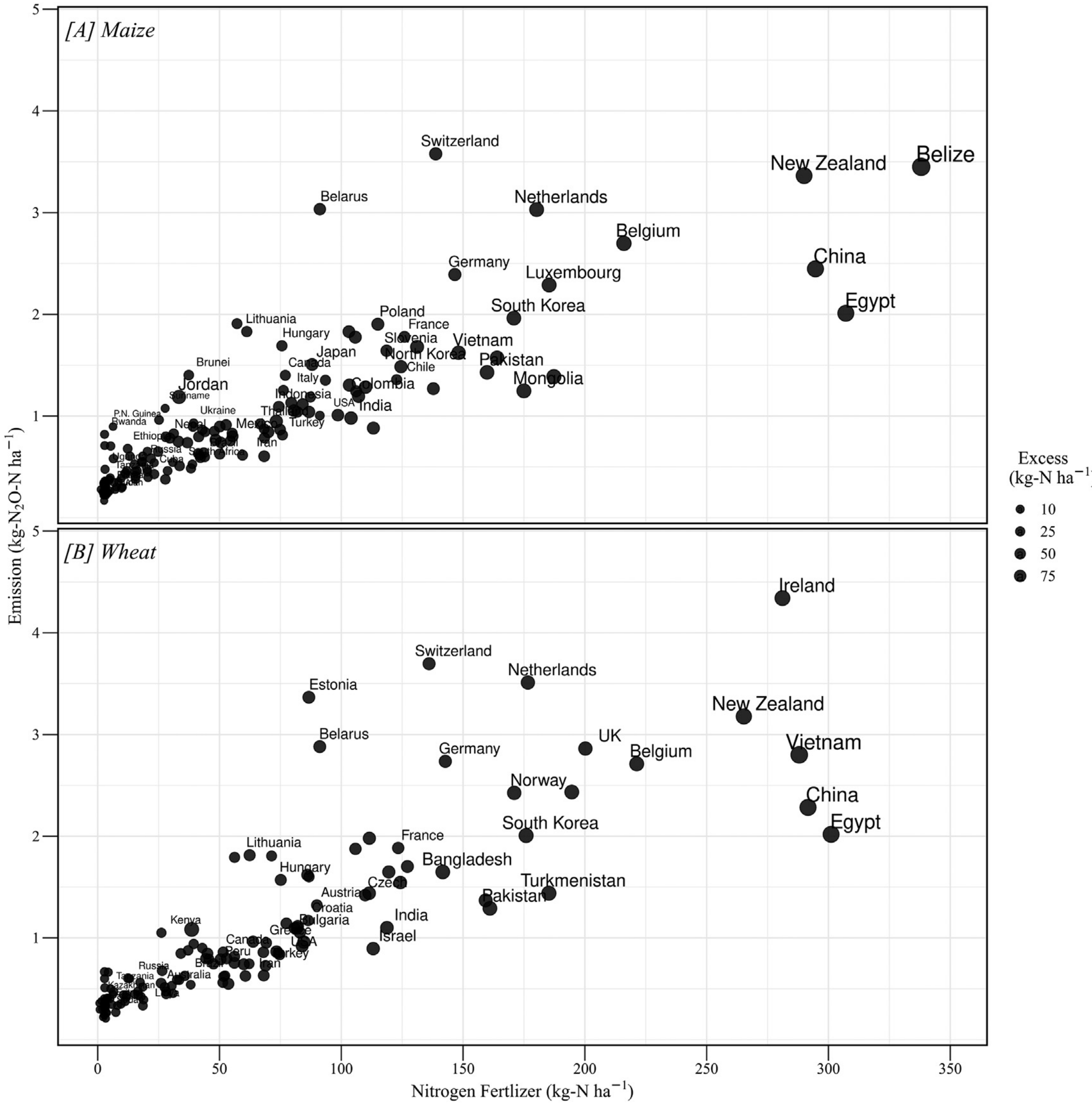

Fig. 5. Synthetic N fertilizer application rates, excess N and N_2O emissions (kg-N_2O-N ha^{-1}) in major (a) maize and (b) wheat growing countries.

better than other models across a range of emission levels. However, the estimation of N_2O emissions using the ensemble of four empirical models minimized the error margins by partially addressing the measurement bias in each model.

4.2. Spatial distribution of N_2O emissions

The spatial distribution of annual N_2O emissions, on a broader scale, is mainly controlled by N fertilizer application rates, and to some extent, by differences in soil properties, cropping intensity and climatic factors (Dhadli et al., 2016; Signor and Cerri, 2013). Our comparisons of models based on the spatial distribution of N_2O emissions showed that IPCC Tier-II had relatively higher emissions than IPCC Tier-I in many areas, particularly in USA, Mexico, Southern Brazil, South East China and parts of Northern Europe. However, IPCC Tier-II estimated smaller N_2O emission values across eastern India and southern Africa than IPCC Tier-I. This could be a result of further disaggregation of emission factors by climate and N source in the IPCC-II method (IPCC, 2019b; IPCC, 2006c).

Climatic factors such as precipitation and temperature affect the biochemical processes that result in N_2O emissions. For example, high temperatures increase the rate of nitrate volatilization which contributes to N_2O emission. A combination of high temperature and N deposition in the soil increases N_2O emissions mainly because both increased N deposition and temperature increase N availability in the soil, the former directly and the latter through increased mineralization rates (Xu-Ri et al., 2012). High precipitation level normally enhances nitrification and denitrification rates and increase N_2O emission. However, precipitation can also limit N_2O emissions in areas where it increases plant growth and N uptake which reduce the supply of substrate for the microbial processes that result in N_2O emissions (Del Grosso and Parton, 2012).

The study indicated clear regional differences in the magnitude of N_2O emissions per unit area from maize and wheat fields. On the continental scale, Asia is the dominant source of N_2O emissions from maize and wheat fields, followed by North America and Europe (Figs. 2 & 4). Although the major hotspots of N_2O emissions from maize and wheat fields are in China and India, emission hotspots are also identified in major producing countries such as USA, Brazil, Germany, France, Ukraine, Russia and Egypt, among others. The results show that high N_2O emissions are mainly driven by the high rate of N fertilizer application in these regions (Fig. 5). High N fertilizer consumption, particularly in South East Asia and South Asia, is prompted by the need to increase productivity to feed the large human population in these regions, as well as by the dietary shift towards more meat and dairy consumption (Foley et al., 2011; Fowler et al., 2013; He et al., 2014; Ladha et al., 2016a, 2016b; Liu and Zhang, 2011; Lu and Tian, 2017; Wu et al.,

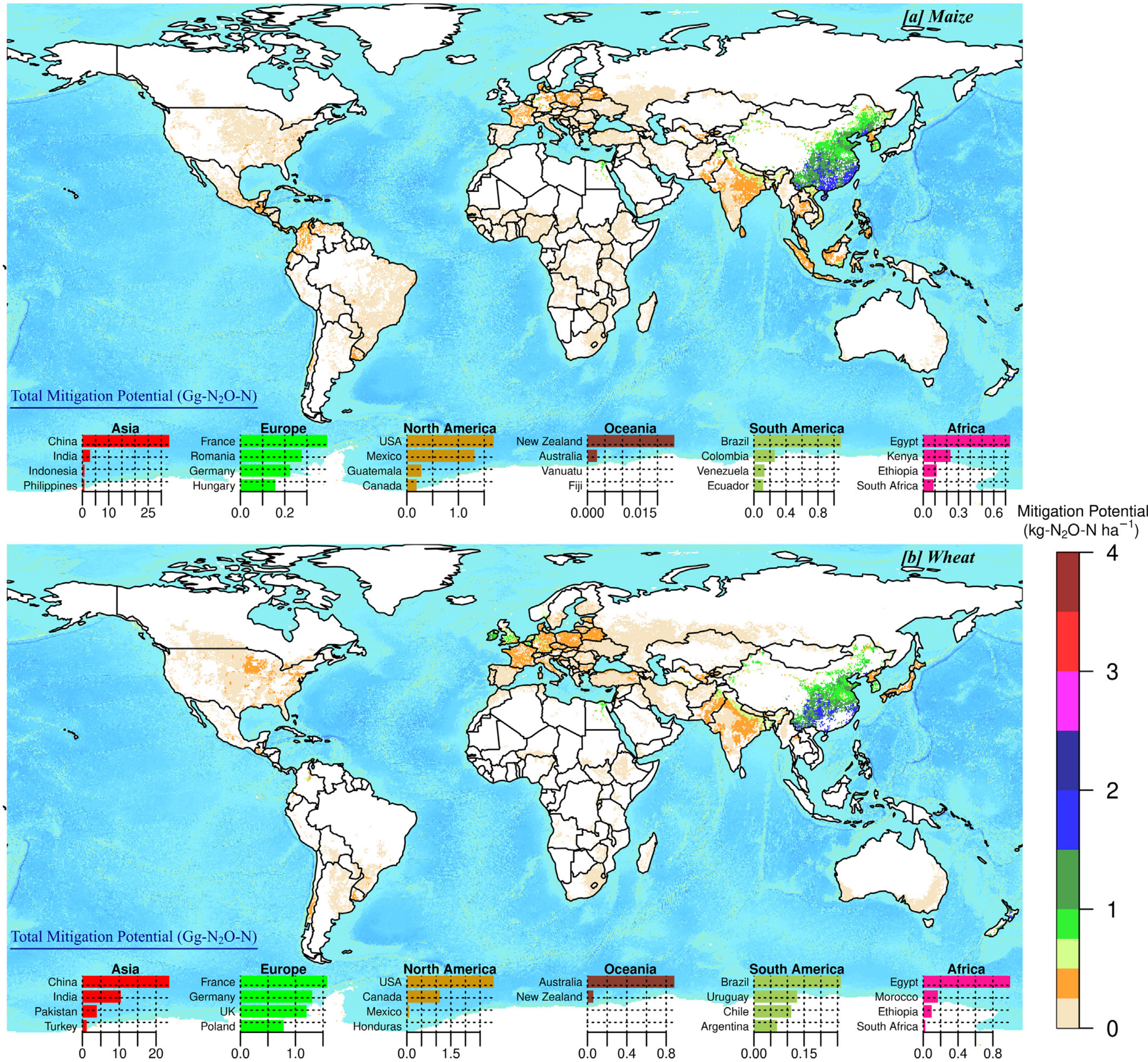

Fig. 6. Spatial distribution of N_2O mitigation potential (kg-N_2O-N ha^{-1}) based on 75% reduction in excess N from (a) maize and (b) wheat fields and annual country total mitigation potential of major countries in Gg-N_2O-N (bar charts) estimated using an ensemble of four empirical models.

2014), as over 60% of the maize produced in this region is used for animal feed. The increasing level of N fertilizer application over time has led to abnormally high N_2O emissions from croplands, making synthetic N fertilizer application a major driver of N_2O emissions in the region (Bijay-Singh, 2017; Chai et al., 2019; Gao et al., 2011; Liu et al., 2013). On the other hand, there is a huge N scarcity of N across the countries in Africa (Liu et al., 2010) (except Egypt), which has led to mining N from diminishing soil pools to grow food (Lu and Tian, 2017; Wang et al., 2017). According to Liu et al., 2010, about 80% of African countries are confronted with nitrogen N scarcity/stress problems, which are often related to the persistent and frequent food insecurity and malnutrition in the region. Most countries in South America also use relatively lower N fertilizer rates compared to other western countries and their Asian counterparts (Houlton et al., 2019). Thus, many parts of South America along with Africa currently have lower N_2O emissions and could be the major options for increasing cereal productivity by transferring N from high application countries to low application ones (Liu et al., 2016). However, some low emission countries in Africa and South America have higher emission intensities (Fig. 3) than high emission countries, indicating the need to increase the marginal rate of yield per unit of additional N input.

Maize and wheat, together with rice, will continue to account for the bulk of the future human food supply (Cassman et al., 2002; Ladha et al., 2016a, 2016b). Therefore, due to the need for increased maize and wheat productivity to support the fast-growing population, N fertilizer consumption is expected to increase dramatically in the near future (Alexandratos and Bruinsma, 2012; FAO, 2004) causing increased N pollution in the environment (Bodirsky et al., 2014). The results of our study suggest that if N_2O emissions from fertilized croplands such as wheat and maize fields are not properly regulated and controlled, they could cancel out the carbon sequestration capacity of forests and grasslands. The results of this study also suggest that if future intensification of agriculture follows the current trend with low nitrogen-use-efficiency, the target of keeping global temperature well below 2 °C by the end of the century (Paris Agreement) could be at a considerable risk.

4.3. Potential for N_2O mitigation

This study estimated the potential for N_2O emissions from maize and wheat fields based on reducing excess N applications while keeping current yield levels. Our results show considerable N_2O emission reduction globally, particularly in those countries and regions where existing N losses and emissions are very high (see Fig. 6). Although limited in spatial coverage, previous studies showed huge (~ 44 Tg yr^{-1}) global total N losses from maize, wheat and rice fields, and the losses were mostly concentrated in China and USA for maize production and China and India for wheat and rice production (Liu et al., 2016). This shows a tremendous potential for improving the efficiency of N use in cereal production in many countries without compromising yield (Liu et al., 2018, Liu et al., 2016) and even increasing it (Mueller et al., 2014; Xu et al., 2015).

As clearly highlighted in this study and previous works (Liu et al., 2018, Liu et al., 2016; Mueller et al., 2014; Wu et al., 2014), the realization of this mitigation potential needs to account for the large regional differences in the sources of emissions and the technological and economic potential of countries to act, and hence our calculation of mitigation potentials at different level of excess N reduction (see Supplementary materials S24 & S25). Since N use efficiency (NUE) of cereal crops is only 33% on a global scale (Edmonds et al., 2009), significant reductions in emissions can be achieved by increasing the NUE of cereal systems. There are many options available to producers that can help them reduce emissions on a unit area and unit product basis. Some of the options suggested for increasing NUE include planting N efficient crops (Hawkesford, 2017); using specially formulated slow-release N fertilizers and nitrification inhibitors (Akiyama et al., 2005; Grant et al., 2020); precision N management through optimal time, rate, and methods of application, integrated use of N fertilizers, manure, and/or crop residue; and optimization of irrigation management (Dobermann and Cassman, 2005; Ladha et al., 2016a, 2016b). Avoiding further intensification in regions where climatic yield potentials are already achieved (> 80%) is also considered as a means to maintain good level of NUE (Liu et al., 2018).

The N_2O mitigation potential from maize and wheat fields varies from place to place and from country to country because of differences in climate and soil factors, production methods, type of farming systems, consumer demand for the crops, and availability of technologies and resources for N management. Compared to many countries such as those in Africa and South America, major maize growing countries like China, USA, Brazil, India, and Mexico and major wheat growing countries such as China, India, USA, France, and Germany are not only N_2O emission hotspots but are also areas with the greatest mitigation opportunities through better N management. This is mainly due to the large areas they allocate to the respective crops and relatively higher levels of N fertilizer use and/or excess N balance in their farming systems. Assuming steady-state conditions in soil organic matter (SOM), the N balance has been proposed as a robust proxy for the amount of N at risk of environmental loss (McLellan et al., 2018). In general, reducing excess N balances through integrated N management will be the entry point for reducing N_2O emissions from crops such as maize and wheat. Recent improvements in NUE in maize and wheat fields in the USA (Lu et al., 2019) and efforts to improve nutrient management in Europe (Van Grinsven et al., 2014) indicate that reduction of N_2O emissions can be achieved if countries put the required policies in place.

The potential for N_2O mitigation can vary with soil type. For example, organic soils have a high emission factor (Shcherbak et al., 2014). Mineralization of organic matter increases the N pool in the soil (Rees, 2011) so that additional N fertilizer application leads to excess N being lost as N_2O into the atmosphere. This situation was observed in some European countries where N_2O emissions were higher than in those countries with higher rates of N application (Fig. 6).

4.4. Policy implications for GHG mitigation in agriculture

One hundred thirty-one countries included agriculture in their Nationally Determined Contributions (NDCs) submitted under the Paris Agreement to the UNFCCC (Richards et al., 2015). About 50% of countries that mentioned mitigation in agriculture targeted fertilizer and cropland management as one of the mitigation options in agriculture. Hotspot countries for N_2O emissions from both maize and wheat cultivation (China, France, Canada, Mexico and Brazil) target fertilizer and cropland management in their NDCs. Some hotspot countries for N_2O emissions from maize (Italy and Romania) and wheat (Germany, Uruguay and Ethiopia) are also considering fertilizer and cropland management as options for GHG mitigation in agriculture. This policy response directly aligns with the need for N_2O mitigation in maize and wheat cultivation. Some hotspot countries such as Australia, New Zealand, Ukraine, Morocco, South Africa, Kenya and Nigeria have included agriculture in their mitigation targets without identifying specific fertilizer management options, whereas countries like India, USA, Russia, Egypt and Uruguay have not targeted agriculture in their GHG mitigation plans.

Locations where crops have both high emissions and high emission intensities (Fig. 7) can be priorities for climate mitigation policies (Carlson et al., 2017). Policies that promote better sources of N fertilizer through regulated standards for fertilizer producers and suppliers could be one option towards improving NUE, reducing excess N and minimizing N_2O emissions. For example, in 2015, the government of India mandated all domestic fertilizer producers to produce 100% neem coated urea which would have huge expected benefits by improving NUE and reducing GHG emissions (GoI, 2019). Improvement and expansion of soil testing and the use of optical sensors as decision support tools where soil testing is not possible can help countries implement site-specific fertilizer management (Basak, 2016; Sharma and Bali, 2018), thereby improving NUE and minimizing N_2O emissions.

5. Conclusion

This study provided a spatial framework for comparing empirical models in estimating N_2O emissions and identified global emission hotspots from maize and wheat fields. Estimation of N_2O emissions using an ensemble of four empirical models minimized the error margins by partially addressing the estimation bias in each model. The study found large disparities in N_2O emissions from maize and wheat fields across regions and countries depending on level of N application rate, soil type, carbon content in the soil, and climatic conditions. At a continental level, Asia is the dominant source of N_2O emission from maize and wheat fields, followed by North America and Europe. High N_2O emissions in maize and wheat production are mainly driven by application of high N fertilizer rates. However, low N fertilizer consuming maize and what fields in Africa and South America have higher emission intensities than those fields in most parts of Asia, Europe and North America where N consumption per unit area is very high. This indicates the need to increase the marginal rate of yield per unit of additional N input in areas where yield gaps are still very high. The results showed a considerable N_2O emission reduction potential globally, particularly in those countries and regions where existing N losses and emissions are very high.

Reducing excess N application on maize and wheat crops through improved NUE can minimize N losses from crop fields and substantially reduce N_2O emissions in many hotspot regions. This reduction can contribute to meeting the mitigation targets that many countries

Fig. 7. Relationship between N_2O emission per unit area and emission intensity across maize and wheat growing countries.

included in their NDCs without compromising food production. The results this study could be used as a baseline for future GHG mitigation efforts from global maize and wheat production systems. This global analysis of emission and mitigation potential across different levels of jurisdiction helps inform policy decisions aimed at fulfilling food security and environmental goals, while also contributing to the global effort of reducing GHG emissions to mitigate climate change. Moreover, the analytical framework and data products used in this study will be helpful for future national, region or global mitigation studies.

Contributions

TBS, KT and CS conceptualized, designed and coordinated the work. RT and KT extracted data, ran the model and performed analysis. TBS, KT and RT drafted the paper. All authors reviewed the manuscript and contributed.

Declaration of competing interest

The authors declare no conflict of interest.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2021.146696.

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